



HAL
open science

Drawing, Handwriting Processing Analysis: New Advances and Challenges

Céline Rémi, Lionel Prevost, Eric Anquetil

► **To cite this version:**

Céline Rémi, Lionel Prevost, Eric Anquetil. Drawing, Handwriting Processing Analysis: New Advances and Challenges. 17th Biennial Conference of the International Graphonomics Society, Jun 2015, Pointe-à-Pitre, Guadeloupe. 2015, 979-10-95177-01-2. hal-01166509

HAL Id: hal-01166509

<https://hal.univ-antilles.fr/hal-01166509v1>

Submitted on 22 Jun 2015

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

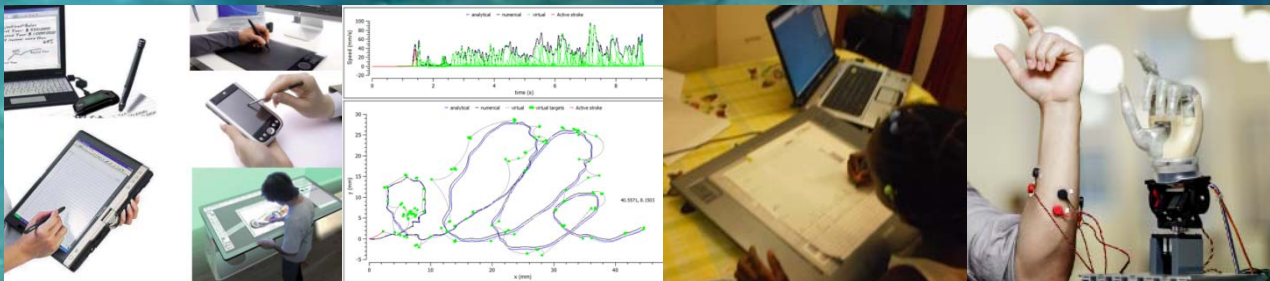


Distributed under a Creative Commons Attribution - NonCommercial - NoDerivatives 4.0 International License

Drawing, Handwriting Processing Analysis:

New Advances and Challenges

*Edited by
C. Rémi, L. Prévost & E. Anquetil*



*Proceedings of the 17th Biennial Conference
of the International Graphonomics Society
Pointe-à-Pitre & Saint-Claude, Guadeloupe, June 21-25, 2015*

Drawing, Handwriting Processing Analysis: New Advances and Challenges

Proceedings of IGS 2015
17th Biennial Conference of the
International Graphonomics Society
21-24 June 2015, Pointe-à-Pitre, Guadeloupe

Edited by

Céline Rémi

University of the French West Indies

Lionel Prévost

University of the French West Indies

Eric Anquetil

INRIA Rennes



**Drawing, Handwriting Processing Analysis: New Advances and Challenges
Proceedings of IGS 2015
Editors: Céline Rémi, Lionel Prévost, Eric Anquetil
ISBN 979-10-95177-01-2**

**Published by:
UNIVERSITE DES ANTILLES
Service commun de la documentation, bibliothèques et édition numériques
Campus de Schoelcher BP 7210 97275 Schœlcher cedex, Martinique
Phone+596-596-72-75-35**

**Contact for Additionnal Copies :
LAMIA
Campus de Fouillole BP 592 97217 Pointe-à-Pitre cedex, Guadeloupe
celine.remi@univ-ag.fr**

Copyright ©2015 by Internation Graphonomics Society and individual authors

**17th Biennial Conference of the
International Graphonomics Society - IGS 2015**

Table of contents

Welcome from the Chairs.....p. 7
Conference Committees.....p. 9
Reviewers.....p. 11
Partners and Sponsors.....p. 12
Program.....p. 15
Invited Presentations.....p. 20

Session 1: Handwriting Analysis and Recognition 1 (Chair : G PIRLO)

Online Sketch Recognition with Incremental Fuzzy Modelsp. 25
Lukas Tencer, Marta Režnáková and Mohamed Cheriet
Feature evaluation for discriminating handwriting fragments.....p. 29
*Claudio De Stefano, Francesco Fontanella, Angelo Marcelli, Antonio Parziale and
Alessandra Scotto di Freca*

Session 2: Medical Applications 1 (Chair : S GAUCHER-CAZALIS)

Predicting Hand Forces from Scalp Electroencephalography During Isometric Grip and Object
Grasping.....p. 33
Andrew Paek, Alycia Gailey, Pranav Parikh, Marco Santello and Jose Contreras-Vidal

Session 3: Education and Handwriting 1 (Chair : C REMI)

Ortho-syllable and syllable affect the dynamics of adjectives handwriting in French.....p. 37
Eric Lambert and Pauline Quémart
How Handwriting Evolves: An Initial Quantitative Analysis of the Development of Indic Scripts..p. 41
Vinodh Rajan

Session 4: Handwriting Analysis and Recognition 2 (Chair : A FISHCHER)

An algorithm based on visual perception of similarity for handwriting comparison.....p. 47
Antonio Parziale, Stanislao Davino and Angelo Marcelli
Recognize multi-touch gestures by graph modeling and matching.....p. 51
Zhaoxin Chen, Eric Anquetil, Harold Mouchère and Christian Viard-Gaudin

The generation of synthetic handwritten data for improving on-line learning.....p. 55
Marta Režnáková, Lukas Tencer, Réjean Plamondon and Mohamed Cheriet

Session 5: Medical Applications 2 (Chair : J VAILLANT)

Omega-Lognormal Analysis of Oscillatory Movements as a Function of Brain Stroke
Risk Factorsp. 59
Albert Bou Hernandez, Andreas Fischer and Réjean Plamondon

Monitoring Neuromotricity On-line: a Cloud Computing Approach.....p. 63
Olivier Lefebvre, Pau Riba, Charles Fournier, Alicia Fornes, Josep Lladós, Réjean Plamondon and Jules Gagnon-Marchand

A neurocomputational model of spinal circuitry for controlling the execution of arm voluntary movements.....p. 67
Antonio Parziale, Jacopo Festa and Angelo Marcelli

Session 6: Education and Handwriting 2 (Chair : J-L VELAY)

Handwriting Analysis with Online Fuzzy Models.....p. 71
Manuel Bouillon and Eric Anquetil

Evaluation of Different Handwriting Teaching Methods by Kinematic and Quality Analyses.....p. 75
Pierluigi D'Antrassi, Agostino Accardo, Paola Ceschia, Iolanda Perrone and Carmen Mandarino

Exploring for scribbling profiles in kindergarten children.....p. 79
Céline Remi, Jean Vaillant, Réjean Plamondon, Lionel Prevost and Thérèse Duval

Session 7: Forensic Sciences 1 (Chair : A MARCELLI)

A Dissimilarity Measure for On-Line Signature Verification Based on the Sigma-Lognormal Model.....p. 83
Andreas Fischer and Réjean Plamondon

Hyper-spectral Analysis for Automatic Signature Extraction.....p. 87
Muhammad Imran Malik, Sheraz Ahmed, Faisal Shafait, Ajmal Saeed Mian, Andreas Dengel, Marcus Liwicki and Christian Nansen

Stability/Complexity Analysis of Dynamic Handwritten Signatures.....p. 91
Giuseppe Pirlo, Donato Impedovo and Tommaso Ferrante

Session 7: Forensic Sciences 2 (Chair : H HARRALSON)

Characteristics of Constrained Handwritten Signatures: An Experimental Investigation.....p. 95
Giuseppe Pirlo, Donato Impedovo and Fabrizio Rizzi

Handwriting and Visual Impairment: A Forensic Analysis of J. S. Bach's Signatures.....p. 99

Heidi H. Harralson, Clare Kaufman and Martin W. B. Jarvis

Training- and Segmentation-Free Intuitive Writer Identification with Task-Adapted
Interest Points..... p. 103

Angelika Garz, Marcel Würsch and Rolf Ingold

A Survey of Forensic Handwriting Examination Research in Response to the NAS Report.....p. 107

Heidi H. Harralson, Elizabeth Waites and Emily J. Will

Poster (Chair : J NAGAU)

Relationships between Handwriting Features and Executive Control among Children with
Developmental Dysgraphia.....p. 111

Sara Rosenblum

The timing of eye-hand movements during signature simulations.....p. 115

Avni Pepe and Jodi Sita

Stress and Motor Learning: Does the Presentation of Physical or Cognitive Stress Influence Motor
Skill Acquisition?.....p. 119

Christopher Aiken, Sarah Odom and Arend Van Gemmert

Subspace method with multi scale wavelet for identification of handwritten lines.....p. 123

Takeshi Furukawa

Haar like features for query by string word spotting.....p. 127

Nicole Vincent, Adam Ghorbel and Jean-Marc Ogier

Writer identification – clustering letters with unknown authors.....p. 131

Johanna Putz-Leszczynska

An assessment of dynamic signature forgery creation methodology and accuracy.....p. 135

Luiz Felipe Belem de Oliveira and Richard Guest

Universum Learning for Semi-Supervised Signature Recognition from Spatio-Temporal Data.....p. 139

Lukas Tencer, Marta Režnáková and Mohamed Cheriet

Welcome from the Chairs

Nous kontan vwè zot

Bienvenue

The Mathematics and Computer Science Lab (LAMIA) is pleased to welcome the 17th edition of the biennial conference of the International Graphonomics Society, IGS2015, hosted by the University of the French West Indies in Guadeloupe from June 21th until the 25th, 2015.

The theme of the IGS for 2015 is “**Drawing, Handwriting Processing Analysis: New Advances and Challenges**”.

We made this choice because drawing and handwriting are communicational skills that are fundamental in geopolitical, ideological and technological evolutions of all time. Primarily used by the Amerindians, one of the very first inhabitants of Guadeloupe, on rocks, today drawing and writing remain the most natural and quick way to signify, express ideas and opinions.

Admittedly, those “basic” graphomotor skills are questioned nowadays and seem to have gone out of use by the new modalities of communication, which were introduced by new technologies and lifestyles.

However, we think that although our societies are interconnected with technology, drawing and handwriting are still useful in defining innovative applications in numerous fields. In this regard, researchers have to solve new problems like those related to the manner in which drawing and handwriting become an efficient way to command various connected objects; or to validate graphomotor skills as evident and objective sources of data useful in the study of human beings, their capabilities and their limits from birth to decline.

Through our lecture we mean to present the challenges that all researchers of the International Graphonomics society are faced with.

During this 17th edition in Guadeloupe, at a disciplinary crossroad-- thanks to the discussions on our respective works -- the purpose will be for us, the members of the community of IGS, to give evidence that new methods of processing and analyzing modalities of action and

expression can contribute, even today, to the opening of new fields of study in hopes of better understanding human beings and advancing our quality of life.

Nine sessions will focus on these objectives throughout the seventeenth edition of the IGS2015 conference.

However, a conference cannot keep all its promises if it is limited to conversations among specialists about learned and scientific things. Therefore, we will have the pleasure to reveal to you a few of the charms of the beautiful archipelago of Guadeloupe; our island welcomes you to partake in social and cultural events which will also include some surprises.

Finally, thanks to the cooperation of French specialists meeting with Guadeloupean actors and families concerned with handwriting learning difficulties, we will try to offer to the participants of IGS 2015 other sources of questioning.

This seemed to us the more obvious Guadeloupe knows numerous difficulties such as the significant rates of which various generations are not using handwriting as an efficient modality of expression and communication. We hope that this open meeting of researchers will be fruitful and will allow its participants to put together the outlines of some solutions.

We express our profound and sincere gratitude towards:

- Pr Rejean Plamondon and Pr Eric Anquetil who respectively accepted to be IGS2015 Honorary Chair and Scientific Chair,
- the three highly skilled scientists : Dr Tracy Ann Hammond, Dr Max Ortiz Catalan and Dr Jean-Luc Velay who give us the honor of accepting the invitation of LAMIA,
- the hundred researchers of more than 15 countries who honored us by submitting their scientific contributions concerning the processes of review, required by the scientific committee of IGS2015 who then, physically or virtually, are able to join us in Guadeloupe.

We also warmly thank all the staffs and services of our rising University of the French West Indies which, in Guadeloupe as in Martinique, brought us generous and enthusiastic assistance to arrange the best conditions for welcome and for the realization of the proceedings of the conference IGS2015.

We wish that the cooperation among each member, despite the recent difficulties within our institution, is the guarantee of a beautiful IGS2015 conference and many more to come.

Conference Committees

Conference Chair

Dr Céline REMI (University of French West Indies)

Conference Co-Chair

Pr Lionel PREVOST (University of French West Indies)

Scientific Chair

Pr Eric ANQUETIL (INRIA Rennes, France)

Honorary Chair

Pr Réjean PLAMONDON (Polytechnique Montréal, Canada)

Program Committee

Adel ALIMI (Tunisia)

Andreas DENGEL (Germany)

Andreas FISCHER (Canada)

Angelo MARCELLI (Italy)

Anna BARNETT (UK)

Annie VINTER (France)

Arend VAN GEMMERT (USA)

Claudio DE STEFANO (Italy)

Guiseppe PIRLO (Italy)

Hans-Leo TEULINGS (USA)

Heidi HARRALSON (USA)

Jose Luis CONTRERAS-VIDAL (USA)

Josep LLADOS (Spain)

Marcus LIWICKI (Germany)

Bilan ZHU (Japan)

Masaki NAKAGAWA (Japan)

Nicole VINCENT (France)

Richard GUEST (UK)

Sara ROSEMBLUM (Israel)

Seiichi UCHIDA (Japan)

Toshiyuki KONDO (Japan)

Umapada PAL (India)

Local organization committee

Dr Suzy GAUCHER-CAZALIS

Dr Enguerran GRANDCHAMP

Dr Jean-Luc HENRY

Dr Jimmy NAGAU

Pr Didier PUZENAT

Dr Audrey ROBINEL

Pr Jean VAILLANT

Reviewers

Giuseppe Pirlo, University of Bari Aldo Moro
Richard Nock, Université des Antilles et de la Guyane
Jean Vaillant, Université des Antilles et de la Guyane
Angelo Marcelli, DIEM - Università di Salerno
Nicole Vincent, Université Paris Descartes Paris 5
Marcus Liwicki, DFKI
Andreas Fischer, École Polytechnique de Montréal
Heidi Harralson,
Richard Guest, University of Kent
Sara Rosenblum, University of Haifa
Hans-Leo Teulings, NeuroScript
Josep Lladós, Computer Vision Center, Universitat Autònoma de Barcelona
Claudio De Stefano, DIEI, Università di Cassino e del Lazio meridionale
Bilan Zhu, Tokyo University of Agriculture and Technology
Jose Contreras-Vidal, University of Houston
Arend Van Gemmert, Louisiana State University
Masaki Nakagawa, Tokyo Univ. of Agri.& Tech.
Umapada Pal, Indian Statistical Institute
Seiichi Uchida, Kyushu University
Andreas Dengel, German Research Center for Artificial Intelligence
Anna Barnett, Oxford Brookes University
Annie Vinter, University of Bourgogne
Toshiyuki Kondo, Tokyo University of Agriculture and Technology
Adel Alimi, REGIM-Lab., ENIS, University of Sfax, Tunisia
Ching Y. Suen, CENPARMI (Centre for Pattern Recognition & Machine Intelligence), Computer Science & Software Engineering Department, Concordia University

Acknowledgements for our partners and sponsors

Silver



International Graphonomics Society

<http://www.graphonomics.org>



-Lab of Mathematics and Computer Science
of the University of French West Indies

<http://lamia.univ-ag.fr/>



-Society Script & Go

<http://www.scriptandgo.com/>



-Communauté d'agglomération Cap Excellence

<http://www.capexcellence.net/>

Bronze



University of French West Indies – <http://www.univ-ag.fr>



Guadeloupean Pole of the University of French West Indies



Guadeloupean Cultural Service of the University of French West Indies

<https://fr-fr.facebook.com/UagPoleGuadeloupeCommissionCulture>

Society Neuroscript



<http://www.neuroscriptsoftware.com/>

Department of Ingenierie of UA

<http://calamar.univ-ag.fr/uag/ingenieur/>



Saint-Claude City - <http://www.ville-saintclaud.fr/>

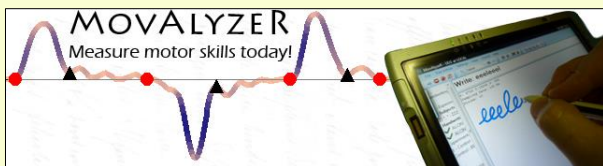
Others



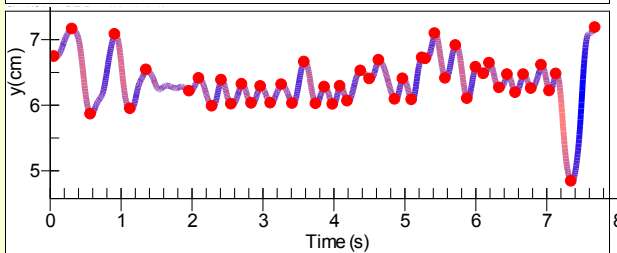
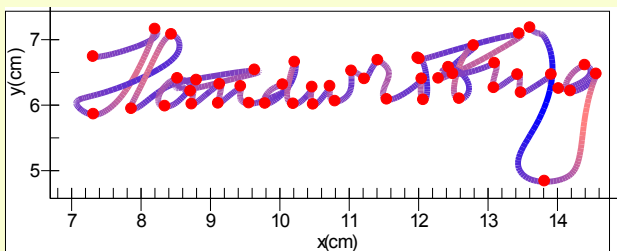
Region Guadeloupe - <http://www.regionguadeloupe.fr>

Handwriting

The most taught motor skill
Yet too little researched



- Pen tablet, touch tablet, mouse
- Import online, offline data
- Audiovisual stimuli, interactive targets
- Experimental settings
- Quantify features
- Integrate external apps, Matlab
- Summarize, visualize, animate
- Norm database
- Multi-site studies



COMPUTER SCIENCE

Artificial Intelligence
Handwriting recognition
Signature verification
Pen tablet testing

[LEARN MORE >>](#)

FORENSICS

Questioned Document Examination
Dynamic and scanned handwriting analysis

[LEARN MORE >>](#)

KINESIOLOGY

Handwriting movement measurement in visuomotor control, biomechanics, ergonomics, psychology, linguistics and human-computer interaction.

[LEARN MORE >>](#)

PSYCHIATRY

Manage side effects of neuroleptics and reduce risks of tardive dyskinesia via quantitative, objective measurements

[LEARN MORE >>](#)

NEUROLOGY

Movement Disorders Movement Exercise
Parkinson's Disease Carpal Tunnel Syndrome
Micrographia Dystonia
Deep Brain Stimulation (DBS)

[LEARN MORE >>](#)

EDUCATION

Child development
Developmental Coordination Disorders (DCD)
Testing handwriting instruction methods

PHYSIOTHERAPY

Occupational therapy Joint hypermobility
Remedial teaching Cerebral palsy
Rehabilitation Acquired brain injury

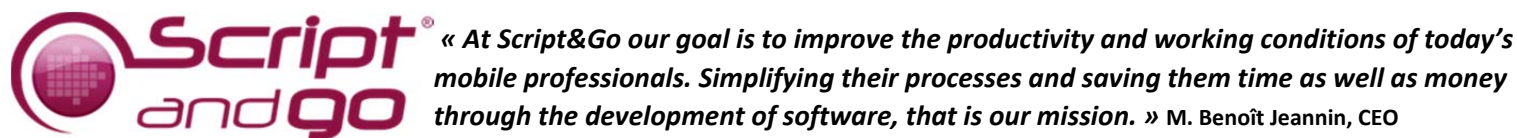
[LEARN MORE >>](#)

NeuroScript

Google: handwriting movement software
www.neuroscriptsoftware.com

Tempe, Arizona, USA
Tel. +1-480-350 9200
Skype: NeuroScript

Script&Go



Based in Rennes, France, the company Script&Go creates solutions on tablets dedicated to mobile professionals and based on writing, gesture and symbol recognition software. These solutions are designed to simulate what you would do on paper, this facilitates digital data entry and communication. Our software also enables you to use diagrams and building plans on site.

Script&Go is a young, growing company which already has solid references and big national clients, especially in the fields of energy, construction, transport and telecom. Besides the success of these professional applications we are also dedicated to



Based on 20 years of research and 6 years of industrial collaboration



Expertise in measuring and tracing hand writing



Includes all the educational exercises for pupils aged 3-7



Trace both finger and stylus

The **project « IntuiScript »** has been selected during the call for the third national project (investments for the future): « innovative services and digital content for learning fundamentals at school » in the sector of E-education. IntuiScript is being developed by the company Script&Go, of which the E-education department is managed by Laure Gilbert, and the research team IntuiDoc (IRISA laboratory) managed by Eric Anquetil, Professor at INSA Rennes.

The objective of the project is to offer an approach dedicated **to learning to write in this digital age** through the use of hybrid tablets (tactile and stylus enabled). The targeted audience are preschools and elementary schools, most notably, **children aged 3 to 7**.

The interesting element of the solution resides in the development of a digitally enriched educational tool which is at the service of current pedagogical practices. This tool is to be easily **remodelled** by the teacher and **personalized** corresponding to the needs of each child.

The tests start in the first semester of 2015 for **a duration of 32 months**, the software will be subjected to a panel of more than 1000 students.



Laure GILBERT
Education project manager – Script&Go

+33.(0)2.30.96.20.62

Eric Anquetil
IntuiDoc team manager – IRISA Rennes

+33.(0)2.99.84.72.38

✉ contact@intuiscript.com

🌐 www.intuiscript.com

PROGRAM AT A GLANCE

Sunday, 21

*L'esplanade
Pointe-à-Pitre
Fouillole*

17H30	Registration
18H00	Welcome Reception
20H00	

Monday, 22

*Pointe-à-Pitre
Fouillole
EH4 room*

08H00	Registration
08H30	Opening Session
09H30	Keynote Speech 1
10H30	Coffee Break
11H	Oral Session 1 Handwriting & Recognition
11H50	Poster and Demo Teaser
12H30	Poster and Demo Session 1
13H00	Lunch
14H20	Keynote Speech 2
15H20	Oral Session 2 Medical Applications
15H50	Poster and Demo Session 2
16H20	Coffee Break
16H50	Oral Session 3 Education & Handwriting
17H40	Pause
18H00	Rencontre autour de l'écriture et ses difficultés
19H30	

Tuesday, 23

09H00	Registration
09H30	Keynote Speech 3
10H30	Coffee Break
11H	Oral Session 5
12H45	Lunch
14H05	Oral Session 6
15H25	Free Time
17H00	Social Program
17H30	Botanical Garden Cocktail
19H00	Gala Dinner
21H30	Bus Departure

Wednesday, 24

*Saint-Claude
Camp Jacob
Amphitheater G
Archimède*

08H00	Touristic Tour
10H00	Coffee Break
10H30	Keynote Speech 4
11H30	Oral Session 7
13H00	Lunch
14H20	Oral Session 8
16H50	Pause
17H00	Award and Closing Session
17H30	Farewell Cocktail
18H30	Bus Departure

Thursday, 25

08H00	Touristic Tour cruising to "Les Saintes"
-------	---

PROGRAM

L : Long presentation (25' + 5'), S : Standard presentation (15' + 5'), Poster and Demo teaser (5')

JUNE, SUNDAY, 21 (*campus of fouillole, l'Esplanade, faculty of science*)

- 17H30 Registration
18H00 **Welcome party**
19H30 Surrounding Caribbean sea, with traditional cocktail and Caribbean Jazz ambiance.

JUNE, MONDAY, 22 (*Campus of Fouillole, Faculty of Science, Méhaut EH4 room*)

- 08H00 Registration
08H30 Opening Session (*Chair C. REMI*)
09H30 **Keynote Speech: Pr. Réjean Plamondon** (*Chair : A MARCELLI*)
Personal digital bodyguard for e-security, e-health and e-learning
10H30 Coffee Break
11H00 **Oral Session 1: Handwriting Analysis and Recognition 1** (*Chair : G PIRLO*)
11H00 L: An Incremental Approach towards Online Sketch Recognition
Lukas Tencer, Marta Režnáková and Mohamed Cheriet
11H30 S: Feature evaluation for discriminating handwriting fragments
*Claudio De Stefano, Francesco Fontanella, Angelo Marcelli, Antonio Parziale and
Alessandra Scotto di Freca*
11H50 **Pause**
12H00 **Poster and Demo Teaser** (*Chair : J NAGAU*)
12H05 Relationships between Handwriting Features and Executive Control among Children with
Developmental Dysgraphia
Sara Rosenblum
12H10 The timing of eye-hand movements during signature simulations
Avni Pepe and Jodi Sita
12H15 Stress and Motor Learning: Does the Presentation of Physical or Cognitive Stress Influence
Motor Skill Acquisition?
Christopher Aiken, Sarah Odom and Arend Van Gemmert
12H20 Subspace method with multi scale wavelet for identification of handwritten lines
Takeshi Furukawa
12H25 Haar like features for query by string word spotting
Nicole Vincent, Adam Ghorbel and Jean-Marc Ogier
12H30 Writer identification – clustering letters with unknown authors
Johanna Putz-Leszczynska
12H35 An assessment of dynamic signature forgery creation methodology and accuracy
Luiz Felipe Belem de Oliveira and Richard Guest
12H40 Universum Learning for Semi-Supervised Signature Recognition from Spatio-Temporal Data
Lukas Tencer, Marta Režnáková and Mohamed Cheriet
12H45 Lunch

- 14H00 **Keynote Speech: Dr. Max Ortiz Catalan**(Chair : A MARCELLI)
Skeletal attachment and neural control of artificial limbs
- 15H00 **Oral Session 2: Medical Applications 1** (Chair : S GAUCHER-CAZALIS)
- 15H00 L: Predicting Hand Forces from Scalp Electroencephalography During Isometric Grip and Object Grasping
Andrew Paek, Alycia Gailey, Pranav Parikh, Marco Santello and Jose Contreras-Vidal
- 15H30 **Poster and Demo Session**
- 16H00 Coffee Break (Poster and Demo Session)
- 16H30 **Oral Session 3: Education and Handwriting 1** (Chair : C REMI)
- 16H30 L: Ortho-syllable and syllable affect the dynamics of adjectives handwriting in French
Eric Lambert and Pauline Quémart
- 17H00 S: How Handwriting Evolves: An Initial Quantitative Analysis of the Development of Indic Scripts
Vinodh Rajan
- 17H20 End of the scientific sessions of IGS2015 first day
- 18H00 **Concomittant to IGS2015 meeting with Guadeloupean actors of handwriting learning and its rehabilitation** (Chair : J-L HENRY)
(Free access – language : French)
Thème : Réalités et défis de l'apprentissage de l'écriture et de la prise en charge de ses difficultés en Guadeloupe
- 19H30

JUNE, TUESDAY, 23 (*Campus of Fouillole, Faculty of Science, Méhaut EH4 room*)

- 09H00 Registration
- 09H30 **Keynote Speech: Dr. Tracy A. Hammond** (Chair : E ANQUETIL)
The personal nature of sketching and the impact of sketch recognition systems
- 10H30 Coffee Break
- 11H00 **Oral Session 4: Handwriting Analysis and Recognition 2** (Chair : A FISHCHER)
- 11H00 L: An algorithm based on visual perception of similarity for handwriting comparison
Antonio Parziale, Stanislao Davino and Angelo Marcelli
- 11H30 L: Recognize multi-touch gestures by graph modeling and matching
Zhaoxin Chen, Eric Anquetil, Harold Mouchère and Christian Viard-Gaudin
- 12H00 L: The generation of synthetic handwritten data for improving on-line learning
Marta Režnáková, Lukas Tencer, Réjean Plamondon and Mohamed Cheriet
- 12H45 Lunch
- 14H00 **Oral Session 5: Medical Applications 2** (Chair : J VAILLANT)
- 14H00 L: Omega-Lognormal Analysis of Oscillatory Movements as a Function of Brain Stroke Risk Factors
Albert Bou Hernandez, Andreas Fischer and Réjean Plamondon
- 14H35 L: Monitoring Neuromotricity On-line: a Cloud Computing Approach.
Olivier Lefebvre, Pau Riba, Charles Fournier, Alicia Fornes, Josep Lladós, Réjean Plamondon and Jules Gagnon-Marchand
- 15H05 S: A neurocomputational model of spinal circuitry for controlling the execution of arm voluntary movements
Antonio Parziale, Jacopo Festa and Angelo Marcelli

15H25 **Free time**

17H00 Bus departure

17H30 Botanical Garden Valombreuse

18H30 Cocktail (+ surprises)

19H30 Gala Dinner

21H45 Bus departure

June, Wednesday, 24 (*Campus Camp Jacob, Amphitheater G Archimède*)

8H00 Bus departure to St-Claude Campus

10H00 Coffee Break / Registration

10H30 **Keynote Speech: Dr. Jean Luc Velay** (*Chair : L PREVOST*)

Translating graphical movements into sounds and music to facilitate handwriting rehabilitation

11H30 **Oral Session 6: Education and Handwriting 2** (*Chair : J-L VELAY*)

11H30 L: Online Handwriting Analysis with Fuzzy Models

Manuel Bouillon and Eric Anquetil

L: Evaluation of Different Handwriting Teaching Methods by Kinematic and Quality Analyses

12H00 *Pierluigi D'Antrassi, Agostino Accardo, Paola Ceschia, Iolanda Perrone and Carmen Mandarino*

12H30 L: Exploring the Kinematic Dimensions of Kindergarten Children's Scribbles

Céline Remi, Jean Vaillant, Réjean Plamondon, Lionel Prevost and Thérèse Duval

13H00 Lunch

14H20 **Oral Session 7: Forensic Sciences 1** (*Chair : A MARCELLI*)

L: A Dissimilarity Measure for On-Line Signature Verification Based on the Sigma-

14H20 Lognormal Model

Andreas Fischer and Réjean Plamondon

14H50 L: Hyper-spectral Analysis for Automatic Signature Extraction

Muhammad Imran Malik, Sheraz Ahmed, Faisal Shafait, Ajmal Saeed Mian, Andreas Dengel, Marcus Liwicki and Christian Nansen

15H20 L: Stability/Complexity Analysis of Dynamic Handwritten Signatures

Giuseppe Pirlo, Donato Impedovo and Tommaso Ferrante

15H50 Pause

14H20 **Oral Session 7: Forensic Sciences 2** (*Chair : H HARRALSON*)

15H50 S: Characteristics of Constrained Handwritten Signatures: An Experimental Investigation

Giuseppe Pirlo, Donato Impedovo and Fabrizio Rizzi

16H10 S: Handwriting and Visual Impairment: A Forensic Analysis of J. S. Bach's Signatures

Heidi H. Harralson, Clare Kaufman and Martin W. B. Jarvis

- 16H30 S: Training- and Segmentation-Free Intuitive Writer Identification with Task-Adapted Interest Points
Angelika Garz, Marcel Wüirsch and Rolf Ingold
- 16H50 S: A Survey of Forensic Handwriting Examination Research in Response to the NAS Report
Heidi H. Harralson, Elizabeth Waites and Emily J. Will
- 17H10 Pause
- 17H30 **Award & Closing Session** (*Chair : R PLAMONDON*)
- 18H00 Farewell Cocktail
- 18H45 Bus departure

Invited Presentations

Prof. Réjean Plamondon, IGS 2015, Honorary Chair

Director, Scribens Lab
Biomedical Science and Technologies Research Centre (GRSTB)
Department of Electrical Engineering,
Ecole Polytechnique de Montréal, Canada
Email : rejean.plamondon @ polymtl.ca



Title: Personal Digital Bodyguards for e-Security, e-Health and e-Learning

Abstract : In the forthcoming years, the ubiquity of hand-held tablets and cell phones, along with their increased computing power and ergonomic data capture performances, will make it possible to convert these devices into **Personal Digital Bodyguards (PDBs)**. PDBs will protect people's sensitive data with signature verification, provide equipment use security with writer authentication, handwritten CAPTCHAs (**e-security**) and perform word spotting and recognition to monitor user fine motor control, which can detect stress, aging and health problems (**e-health**). In the hands of children, these tools will turn into toys helping them to learn and master their fine motricity and become better writers and students (**e-learning**).

At Scribens laboratory, we have been working on some of these potential applications for many years, directly or indirectly guided by the **Lognormality Principle**. In its simplest form, this fundamental premise states that **the lognormality of the neuromuscular impulse responses is a basic global feature reflecting the behaviour of individuals who are in perfect control of their movements**. As a corollary, if we specifically focus on the basic mathematical convergence toward lognormality, motor control learning in young children can be interpreted as a migration toward lognormality. Then, for the greater part of their lives, human adults take advantage of lognormality to control their movements. Finally, as aging and health issues increase, a progressive departure from lognormality is anticipated.

From a practical point of view, the concept of lognormality provides a common thread, an integrative standpoint to track the problems of signature verification, writer identification, handwriting generation, recognition and learning. This keynote presentation will point out how the resulting methodologies could be of great help to meet the PDB challenge. It will highlight which pathways we have decided to follow to reach this goal, where we stand now and what should be our next moves. Throughout the talk, the worldwide collective efforts that we have initiated to track some specific problems will be pointed out, emphasizing the specific expertise of our national and international partners.

Biography: Réjean Plamondon received a B.Sc. degree in Physics, and M.Sc.A. and Ph.D. degrees in Electrical Engineering from Université Laval, Québec, P.Q., Canada in 1973, 1975 and 1978 respectively. In 1978, he joined the faculty of the École Polytechnique, Université de Montréal, Montréal, P.Q., Canada, and became a Full Professor in 1991. He has been Head of the Department of Electrical and Computer Engineering from 1996 to 1998 and President of École Polytechnique from 1998 to 2002. He is now Head of Laboratoire Scribens at this institution. Along the various stages of his career, Professor Plamondon have been working in Pattern Recognition particularly on the study of emerging phenomena and behavior in biological and physical systems exploiting various convergence

theorems. Over the last thirty years, Professor Plamondon has been involved in many pattern recognition projects, particularly in the field of on-line and off-line handwriting analysis and processing. He has proposed many original solutions, based on exhaustive studies of human movement generation and perception, to problems related to the design of automatic systems for signature verification and handwriting recognition, as well as interactive electronic pen pads to help children learning handwriting and powerful methods for analyzing and interpreting neuromuscular signals. His main contribution has been the development of a kinematic theory of rapid human movements which can take into account, with the help of a unique set of lognormal functions, the major psychophysical phenomena reported in studies dealing with rapid movements. The theory has been found successful in describing the basic kinematic properties of velocity profiles as observed in finger, hand, arm, head and eye movements. Professor Plamondon has studied and analyzed these bio signals extensively in order to develop creative and powerful methods and systems in various domains of engineering. In the last twelve years, he has also been deeply involved in the generalization of his kinematic theory to the study of emerging phenomena in physical systems, mainly focussing on the unification of general relativity and quantum mechanics. He published, in June 2012, "Patterns in Physics: Toward a Unifying Theory," a book on this topic, and recently summarized the conducting thread used all along his research career in "Strokes against Stroke, Strokes for Strides, Pattern Recognition, vol.47, No.3, pp. 929-944. Full member of the Canadian Association of Physicists, the Ordre des Ingénieurs du Québec, the Union nationale des écrivains du Québec, Dr Plamondon is an also active member of several international societies. He is a lifelong Fellow of the Netherlands Institute for Advanced Study in the Humanities and Social Sciences (NIAS; 1989), of the International Association for Pattern Recognition (IAPR; 1994) and of the Institute of Electrical and Electronics Engineers (IEEE; 2000). From 1990 to 1997, he was the President of the Canadian Image Processing and Pattern Recognition Society and the Canadian representative on the board of Governors of IAPR. He has been the President of the International Graphonomics Society (IGS) from 1995 to 2007. He has been involved in the planning and organization of numerous international conferences and workshops and has worked with scientists from many countries all over the world. He is the author or co-author of more than 300 publications and owner of four patents. He has edited or co-edited five books and several Special Issues of scientific journals. He has also published a children book, a short story and three collections of poems. He recently received the IAPR/ICDAR 2013 outstanding achievement award "for theoretical contributions to the understanding of human movement and its applications to signature verification, handwriting recognition, instruction, and health assessment, and for promoting on-line document processing in numerous multidisciplinary fields."

Jean-Luc Velay

Cognitive Neurosciences Laboratory member,
CNRS Researcher
Aix-Marseille University
Email : jean-luc.velay @ univ-amu.fr



Title: Translating graphical movements into sounds and music to facilitate handwriting rehabilitation

Abstract: The mastering of handwriting is so essential in our society that it is important to try to find new methods for facilitating its learning and rehabilitation. Up to now, the quality of handwriting was evaluated from the visual inspection of its legibility and not from the movement that generates the trace, although the ability to control the graphic movements clearly impacts on the quality of the writing. New technologies improve existing techniques or enable new methods to supply the therapist with new diagnostic tools and the writer with real-time computer-assisted feedback. In particular, sounds can be used to inform about the correctness of an ongoing movement, without directly interfering with the visual and proprioceptive feedback. Furthermore, the dynamic features of sounds make them particularly appropriate means of accessing the spatiotemporal characteristics of movements. Finally, because of their playful characteristics, sounds are potentially effective for motivating children in particular need of such assistance. We will present experimental data suggesting that transforming kinematic variables into sounds might be a relevant tool allowing a therapist to complete the visual assessment of the written trace by an auditory control of the handwriting movement quality. Furthermore, both adults with a proprioceptive loss and dysgraphic children are able to write faster and with more fluent movements with the aid of auditory feedback. We propose that sounds and music may be used as a palliative way to assist handwriting movement learning and rehabilitation.

Biography : I received a Ph.D. degree in Neurosciences from Aix-Marseille University, France in 1984. After a post-doctoral training under the supervision of P. Viviani in Milan (Italy) where I studied visual perception and oculomotor control, I was recruited as permanent senior researcher by the French *Centre for Scientific Research* (CNRS) in 1986. I am currently in the Cognitive Neurosciences Laboratory in Marseille. During several years, I have been studying the role of arm and eye proprioception both in motor control and space perception in Human. I became interested in the control of a particular movement serving language, namely handwriting. Using fMRI, I try to understand the cognitive and brain processes involved in handwriting production and perception, and the interconnections between reading and handwriting. In particular, we have studied the cognitive and cerebral consequences of the increasing moving from handwriting to typing. In addition, I have been working on the handwriting troubles and their links with other learning troubles, as dyslexia and developmental coordination disorders (DCD). An important topic in our team is the relationships between music production and perception and oral and written language: We used music as a means of reducing language troubles in dyslexic children, for instance. By nature, handwriting is an inter-disciplinary subject which led me to create multiple collaborations with Education Sciences, Educational psychology, linguistics, neurologists, forensic sciences... Recently, we were looking for the best strategy to inform poor writers about the quality of their writing movements. Thanks to a collaboration with acousticians, we transformed some kinematic variables into sounds to supply them with a bio-feedback about handwriting. This approach seems promising to help children with dysgraphia to better feel what is not appropriate in their movements. I co-hosted the IGS2009 Conference in Dijon (France) together with A. Vinter.

Max Ortiz Catalan

Chalmers University of Technology

Email : maxo @ chalmers.se



Title: Skeletal attachment and neural control of artificial limbs

Abstract: Ever since the invention of implantable devices, a reliable and long-term stable communication with the outside of the body has been a major problem. In the case of prosthetic limbs, this has prevented the utilization of implanted neuromuscular interfaces for a direct and intuitive neural control. Our group at Chalmers University of Technology, the Centre of Orthopaedic Osseointegration at Sahlgrenska University Hospital (COO-SUH), and Integrum AB, has developed a bidirectional interface into the human body, namely the Osseointegrated Human-Machine Gateway (OHMG). The OHMG allows for the long-term study of bioelectric signals directly recorded from nerves and muscles of patients with missing limbs, as well as to chronically elicit tactile sensory feedback via neurostimulation. More importantly, results from the first patient have shown to dramatically increase prosthetic functionality, thus reducing disability and improving quality of life (video 1, 2). This patient is the first person in the world to have permanently implanted electrodes in nerves and muscles to control a robotic prosthesis at home and work, but more importantly, he has done so for two years without complications, thus demonstrating the feasibility of this novel technology.

This talk will focus on the bidirectional osseointegrated interface, neurostimulation for sensory feedback, and pattern recognition for control (video 3), as well as our latest work on a novel treatment of phantom limb pain using virtual and augmented reality (video 4).

Biography: Dr. Max Ortiz Catalan received his Electronics Engineering degree in 2005 by the ITESM Campus Toluca, Mexico. He spent one year of his engineering formation at the Université de Technologie de Compiègne, France. He worked 2 years in industrial automation before joining the M.Sc. program in Complex Adaptive System, at Chalmers University of Technology (CTH), Sweden, graduating in 2009. In 2014, he obtained his PhD in Biomedical Engineering from CTH in collaboration with the Centre of Orthopaedic Osseointegration at Sahlgrenska University Hospital (COO-SUH), and Integrum AB, Sweden. During his PhD, he was invited researcher at Neural Rehabilitation Engineering Lab in the Université catholique de Louvain, Belgium, and Research Engineer at Integrum AB. He is currently Research Scientist at CTH and COO-SUH, as well as R&D Manager at Integrum AB. His research interests include bioelectric signals acquisition electronics (analog and digital); signal processing and artificial intelligence algorithms for pattern recognition and control; neuromuscular interfaces; bone-anchored prostheses and osseointegration; as well as virtual and augmented reality for neuromuscular rehabilitation and the treatment of phantom limb pain.

He has won several academic and industrial awards such as “Leadership and Academic Excellence” by ITESM, Mexico; the “Young Scientist Forum Scholarship” by GöteborgBio, Sweden; the youngest recipient of the “You Can Make a Difference Award” by one of the world’s largest transnational companies; and the “European Youth Award” by the European Council.

Dr. Tracy Anne Hammond

Director, Sketch Recognition Lab
Associate Professor
Computer Science & Engineering, TAMU
Email: hammond @ tamu.edu



Title: The Personal Nature of Sketching and the Impact of Sketch Recognition Systems

abstract: Drawing is one of our most natural forms of communication. We use it from an early age, and throughout life, it remains an important means of expression. At the Sketch Recognition Lab, we have found enormous potential in enabling computers to understand and act upon this expression, and in this talk, we'll explore how sketch recognition is already having an impact in many fields today. Because it is so intuitive, educational software using sketch recognition can remove many of the limitations faced by other computer-based learning tools. Mechanix, an educational tool for automatically evaluating trusses and free body diagrams, is built around this principle. Mechanix's live interaction helps students learn best practices and how to avoid common mistakes from their first experience with a new concept. Other systems like iCanDraw and Persketchtivity use their understanding of students' drawings to help them learn design principles and improve their skill. Each of these applications relies on a personal interaction with the user to provide them with an enhanced learning experience, but this connection carries information beyond the field of education. In health, recognition algorithms can be applied to user sketches to track their developmental level, sleepiness, or mental health, as SmartStrokes does for patients recovering from strokes. Related to forensics, marks as small as the dotting of an "i" can be used by a computer to identify, with high accuracy, the individual who drew it based on a number of features. Sketch recognition and the algorithms it uses have potential for tremendous impacts on our lives by taking our interactions with technology to the next level.

Biography: Director of the Sketch Recognition Lab and Associate Professor in the Department of Computer Science and Engineering at Texas A&M University, Dr. Hammond is an international leader in activity recognition (focusing on eye, body, and sketch motions), haptics, intelligent fabrics, SmartPhone development, and computer human interaction research. Dr. Hammond's publications on the subjects are widely cited and have well over a thousand citations, with Dr. Hammond having an h-index of 18, an h10-index of 26, and four papers with over 100 citations each. Her research has been funded by NSF, DARPA, Google, and many others, totaling over 3.6 million dollars in peer reviewed funding. She holds a PhD in Computer Science and FTO (Finance Technology Option) from MIT, and four degrees from Columbia University: an M.S in Anthropology, an M.S. in Computer Science, a B.A. in Mathematics, and a B.S. in Applied Mathematics. Prior to joining the TAMU CSE faculty Dr. Hammond taught for five years at Columbia University and was a telecom analyst for four years at Goldman Sachs. Dr Hammond is the 2011-2012 recipient of the Charles H. Barclay, Jr. '45 Faculty Fellow Award. The Barclay Award is given to professors and associate professors who have been nominated for their overall contributions to the Engineering Program through classroom instruction, scholarly activities, and professional service. Dr. Hammond has been featured on the Discovery Channel and other news sources.

Online Sketch Recognition with Incremental Fuzzy Models

Lukas TENCER ^a, Marta REŽNÁKOVÁ ^a and Mohamed CHERIET ^a

^a *École de technologie supérieure (Département de Génie de la Production Automatisée)
1100 Rue Notre-Dame Ouest
H3C 1K3, Montreal, CANADA*

Abstract. In this paper, we present a novel method for recognition of handwritten sketches. Unlike previous approaches, we focus on online retrieval and ability to build our model incrementally, thus we do not need to know all the data in advance and we can achieve very good recognition results after as few as 15 samples. The method is composed of two main parts: feature representation and learning and recognition. In feature representation part, we utilize SIFT-like feature descriptors in combination with soft response Bag-of-Words techniques. Descriptors are extracted locally using our novel sketch-specific sampling strategy and for support regions we follow patch-based approach. For learning and recognition, we use a novel technique based on fuzzy-neural networks, which has shown good performance in incremental learning. The experiments on state-of-the-art benchmarks have shown promising results.

1. Introduction

"It is better to see once than to hear a hundred times." Is saying old Russian proverb, which clearly favors visual form of communication. Since ancient times, it was specifically sketch, which allowed people to communicate visual information, record memories. Even after thousands of years, sketching is one of few ways, how majority of people can render their mental images (see Fig. 1). Since direct visualization of mental images using "mind-reading" techniques is clearly progressing (Miyawaki et al., 2008). Though they are far away from practical use and therefore sketch is the momentarily the best option for a human being to capture mental image. Also, as proved by recent research results (Walther, Chai, Caddigan, Beck, & Fei-Fei, 2011), sketches are sufficient enough to create stimuli at the same level as real-world images. This fact also justifies our choice of features based on edges.

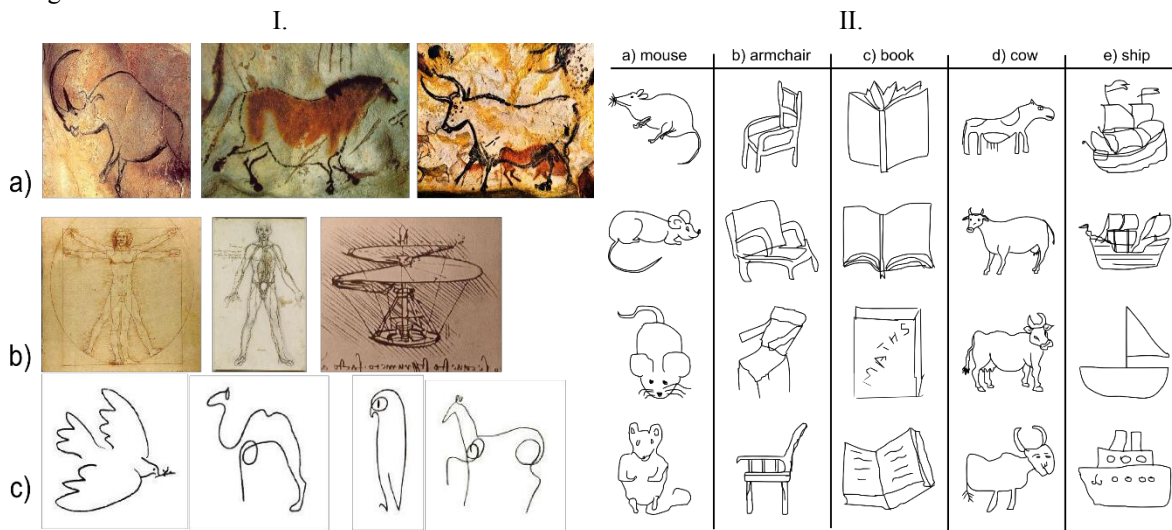


Figure 1. I. Sketches through the history. a) cave painting b) sketches from Leonardo da Vinci c) sketches from Pablo Picasso; II. Examples from our database

Unlike batch approaches, our approach does not rely on the fact, that the whole dataset is available a priori. In real-world, applications should be adaptable to the user, and it should be intelligent to learn new examples. To have one model, which represents the system "forever" is not feasible. As the user is using the sketching system more and more, his performance improves and the old model becomes obsolete and cannot capture user's performance anymore, as noted before for gestures. Therefore, we aim to develop a model, which can learn incrementally and adapt to user's drawing performance. At last, even though prior works did have available wide variety of data, this statement is not always true for commercial applications. Once sketch-based interaction is integrated into the system, it needs to capture user's sketching performance as soon as possible, with minimum number of examples. Therefore, our second motivation in the learning part of our work is to learn from scratch, with a minimum amount of prior learning data.

Prior works in the area of sketch-based focused mostly on area-specific recognition of sketches within very limited domain. These include user interfaces, chemical diagrams, architectural designs, faces or mathematical

equations (Caetano, Goulart, Fonseca, & Jorge, 2002) (Ouyang & Davis, 2007) (Tang & Wang, 2004) (Jr & Zeleznik, 2007). Therefore presence of structure and prior knowledge about the domain allows high recognition rates in these cases. Other prior works focused on more general applications and they approached sketch recognition independent of the domain of application. These techniques, are usually based on graphical models (T. Sezgin & Davis, 2007) (T. M. Sezgin & Davis, 2008) (T. M. Sezgin & Davis, 2005) (Alvarado & Davis, 2004) and require significant amount of data during the training phase, or they generate training data artificially by applying noise function to examples (T. M. Sezgin & Davis, 2005). Since we are aiming incremental learning, none of these approaches satisfies our primal condition on a good performance with a low amount of data. The most advanced approach so-far was introduced by Eitz (Eitz, Hays, & Alexa, 2012), although this one processed images in batch-manner; thus no incremental learning was performed.

2. Sketch Representation

As an input for our recognition system at learning and recognition stages is a binary image, which represents sketched image. In our method we focus on descriptors, which emphasize information abundant in sketches, that is edge orientation. After experimentation with various descriptors (Histogram Of Gradients (HOG), Edge Histogram Descriptor (EHD)), we observed best results for Scale Invariant Feature Transform (SIFT) descriptor and therefore we decided to use it in our method. Although original SIFT method as presented by (Lowe, 2004) is composed of two separate parts, interest point detection and feature extraction, we need to adapt the original technique for application to sketched images.

Our proposed descriptor is patch-based and calculated on local support region. Since many previous applications used densely sampled small regions, in case of sketches we need to lean toward larger support regions, because small regions do not capture sufficient amount of sketched regions. Size of our region depends on size of the image and amount of sampled points, so that area covered by sampled patches is about $Q = 50$ times the size of the image ($p_width, p_height = \sqrt{(img_size^2 \cdot Q)/n_points}$). We have experimented with different amounts of sampled area and we have found minimal gain in increase over 50, although an increase in computational cost was significant. This yields for images of size 256×256 as they are stored in testing dataset, size of support region that accounts for 9% of total image area for each patch, which is at size of about 70 pixels with 600 sampled interest points.

Our main adaptation for SIFT-like descriptors for sketches lies in a change of interest point detector. As noted by (Eitz, Hildebrand, Boubekeur, & Alexa, 2010), most prominent interest points lies on sketched lines. We would like to add an assumption, that it is also in between and in close distance to sketched lines, where we can find fine regions to sample interest points. Therefore we propose interest point detector, based on importance sampling on, between and around sketched lines, with a soft gradient between importance of different regions.

Once we have obtained sampled interest points, we calculate a descriptor on a given support region. We subdivide the image into 4×4 grid and calculate orientation histogram for each of the regions. Final descriptor is created by concatenation of the histograms for all of the regions, contribution of each pixel to the histogram of the region is weighted by Gaussian placed in the middle of the region. Normalization is applied to achieve better scale invariance. The final representation of the image is then collection of features $F = \{f_i\}$, where f_i is descriptor extracted for single local patch.

The final descriptor for representing sketches is calculated based on bag-of-words representation. For this representation, we first need to acquire a visual codebook, which we will use to encode the sketch. We construct the visual codebook by clustering the space of descriptors into k disjunct clusters, so the inner cluster scatter is minimal. The vocabulary of visual words is then represented as $V = \{v_i\}$.

Once we obtain V , then we can represent the image as a frequency histogram of visual words, where each extracted descriptor is assigned to the nearest bin given L_2 distance. Although this can be further improved by considering "soft" response histogram. In this version of the descriptor, not frequency is stored, but the relative distance to each of the visual words, this is accumulated for all the extracted local patches. Gaussian kernel is used to determine the distance between visual word and a given sample.

3. Sketch Recognition

For the recognition part, we use an online learning model, where the samples are learned incrementally and inference is calculated in real time. Thus, we will divide this section into learning and inference and describe the method used for this work. The whole model described in this paper is a hybrid ART (Adaptive Resonance Theory) and TS (Takagi-Sugeno) fuzzy neural networks originally created for online handwritten recognition.

Learning of the model is composed of two parts: generating rules for TS network and learning parameters of the rules. Generation of the rules is thus driven by ART-2A neural network, which is self-adaptive unsupervised clustering method. Here, the number of rules is not necessary set and does not equal the number of classes in the system. This is following the fuzzy logic, where all classes are defined by the possibility of occurrence within each rule.

The learning process of rule manipulation is based on an update of committed rule in a case of resonance and generating of a new rule in a case of reset. To decide this, a choice function (1) is compared with a vigilance ρ . If (2) is satisfied, resonance occurs, otherwise the reset is detected.

$$t_j = \begin{cases} x \cdot w_j & \text{if } j \text{ is index of committed node} \\ \alpha \cdot \sum_{k=1}^d i_k & \text{if } j \text{ is index of uncommitted node} \end{cases} \quad (1)$$

$$T_j = \max_j t_j \geq \rho \quad (2)$$

Then, the rule to be updated is either winning one (if resonance) or a new rule (if reset) and the update is performed (3), where w_j is a weight vector and λ a learning parameter.

$$w_j^{new} = \mathcal{N}(\lambda \cdot x + (1 - \lambda) \cdot w_j^{old}) \quad (3)$$

After clustering updates, the TS network is to be learned. Each rule is in a form of (4), where both IF and THEN (antecedent and consequent) parts are learned separately. For antecedent part, we are using the incremental density update (5-7).

$$R_i: \text{IF } x \text{ is } P_i \text{ THEN } y_i^1 = \pi_i^1 x, \dots, y_i^c = \pi_i^c x \quad (4)$$

$$\beta_i = \frac{N_i}{N_i + N_i \alpha_i - 2x \rho_i + \gamma_i} \quad (5)$$

$$N_i = N_{i,old} + 1 \quad (6)$$

$$\alpha_i = x^2 \quad (7)$$

$$\gamma_i = \gamma_{i,old} + x_{old}^2 = \gamma_{i,old} + \alpha_{i,old}, \quad \gamma_{i,init} = 0$$

$$\rho_i = \rho_{i,old} + x_{old}, \quad \rho_{i,init} = 0$$

When learning the THEN part, the learning is not competitive as in the previous parts, but based on fuzzy logic. Thus, for each sample all the rules are updated with a proper increment (8-9).

$$\Pi_i = \Pi_{i,old} + C_i \beta_i x (y - \Pi_{i,old} \beta_i x); \quad \Pi_i = \{\pi_i^j\} \quad (8)$$

$$C_i = C_{i,old} - \frac{C_{i,old} \beta_i x \beta_i x^T C_{i,old}}{1 + \beta_i x^T C_{i,old} \beta_i x} \quad (9)$$

The inference is based purely on TS fuzzy network, where as shown in (4), the fuzzy results of each rule y_i^j are calculated as linear combinations of proper parameters and input sample. Then, their results are weighted by the antecedent density (5) and a final inference for every class in the system is derived (10). Then the choice of the winning class is set by the maximum over all such inferences.

$$y^j = \sum_{i=1}^r \beta_i \pi_i^j x \quad (10)$$

5. Experiments and Results

In this work, we have used state-of-the-art dataset of sketched images collected by Eitz (Eitz et al., 2012). It consists of 20,000 sketches in 250 categories (see Fig. 1). Categories consists of objects regularly encountered in everyday life and are aimed to capture general semantics of objects. Best reported results on this dataset are by (Eitz et al., 2012) at 56% (where chance is 4%), although it processes the data in batch manner, not in incremental manner.

We evaluate the performance of our system during the whole process of learning, thus precision should be high with every incoming sample. As evaluation criterion, we use several metrics. First criterion is simple accuracy evaluated as a ratio correctly classified element over total number of processed elements until current time t_i . In second criterion, we change the success recognition criterion. We consider an example to be recognized correctly, if correct label is one of first n returned examples, where n is set to be 2% of total number of classes. At last, we use fall-off function to increase the effect of recent errors and decrease penalization for errors, which happened in a distant past. We use two falloff functions, linear and Gaussian with a cut-off threshold at 95% of values.

As we can see Fig. 2, our results are very promising, although at the beginning of the training the performance is low. This is mostly due to low number of examples present for a given class. Also according to our observations, errors are more frequent, when new class is introduced. Using evaluation criterion of top n samples, we can see increased accuracy, even at the beginning of training. One can observe qualitative results in Fig. 2. where we present top n labels for selected queries. At last, we can see the recognition rate for the whole learning process in Fig. 2. Decreased performance in the beginning is caused by insufficient number of labeled samples.

Our method is capable of performance in real-time and execution of incremental learning and recognition of a single example takes about 340ms on standard desktop PC.

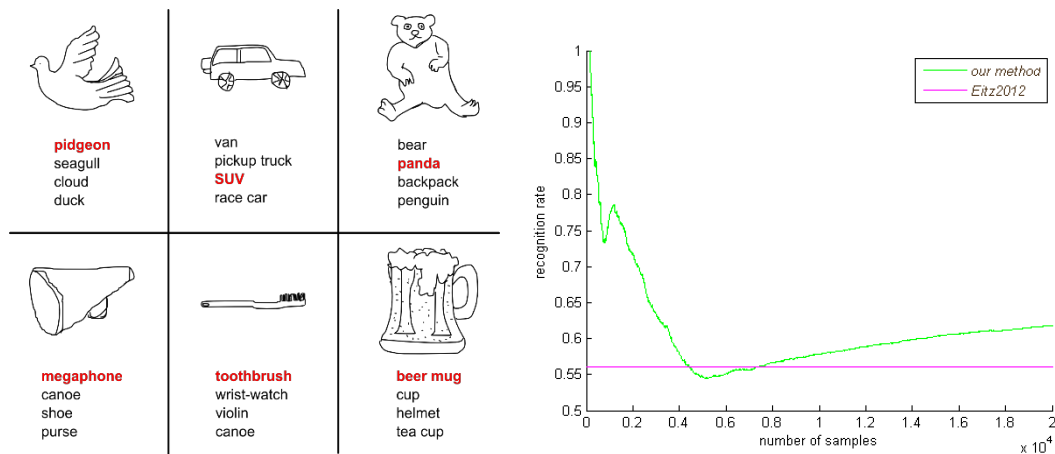


Figure 2. a) Results of the recognition algorithm, showing top 4 results. True label is highlighted in red. b) And Recognition rate evaluation, comparison of our method and the best result of state-of-the-art Eitz2012 method

6. Conclusion and Future Work

We presented a method capable of retrieval of sketched objects of everyday life. This method can process incoming data in incremental manner and is capable of learning the representation of classes in interactive and on-line mode. This is achieved through a combination of special sketch-specific features and incremental fuzzy-neural learning method. Up to our knowledge, there is no state-of-the-art method capable of incremental learning of sketched images, which can over-perform our technique.

Although our system is working in incremental manner, it still needs pre-processing to obtain the codebook. To remove this obstacle we need to devise an efficient unsupervised incremental learning algorithm, so besides incremental learning in feature space, we can also construct incrementally the visual codebook. Also the representation of the codebook itself is shallow, and we may consider higher level hierarchy to represent composite primitives as hierarchy levels in the codebook, so we can achieve higher rate of recognition. At last we are looking into combining visual and semantic retrieval for sketch-based image recognition, thus we will develop an approach to combine these two slightly distant metaphors.

The authors would like to thank to SSHRC Canada and NSERC Canada for their financial support.

References

- Alvarado, C., & Davis, R. (2004). SketchREAD: a multi-domain sketch recognition engine. *Proceedings of the 17th Annual ACM Symposium ...*, 6(2).
- Caetano, A., Goulart, N., Fonseca, M., & Jorge, J. (2002). Javasketchit: Issues in sketching the look of user interfaces. *AAAI Spring Symposium*
- Eitz, M., Hays, J., & Alexa, M. (2012). How do humans sketch objects? *ACM Transactions on Graphics (TOG)*, 31(4), 1–10.
- Eitz, M., Hildebrand, K., Boubekeur, T., & Alexa, M. (2010). Sketch-Based Image Retrieval: Benchmark and Bag-of-Features Descriptors. *Visualization and Computer Graphics, IEEE Transactions on*, 17(11), 1624–1636.
- Jr, J. L., & Zeleznik, R. (2007). MathPad 2: a system for the creation and exploration of mathematical sketches. *ACM SIGGRAPH 2007 Courses*.
- Lowe, D. G. (2004). Distinctive Image Features from Scale-Invariant Keypoints. *International Journal of Computer Vision*, 60(2), 91–110.
- Miyawaki, Y., Uchida, H., Yamashita, O., Sato, M., Morito, Y., Tanabe, H. C., ... Kamitani, Y. (2008). Visual image reconstruction from human brain activity using a combination of multiscale local image decoders. *Neuron*, 60(5),
- Ouyang, T., & Davis, R. (2007). Recognition of hand drawn chemical diagrams. *Proceedings of the National Conference on Artificial ...*, 846–851.
- Sezgin, T., & Davis, R. (2007). Sketch interpretation using multiscale models of temporal patterns. *Computer Graphics and Applications*, ..., (February), 28–37.
- Sezgin, T. M., & Davis, R. (2005). HMM-based efficient sketch recognition. In *Proceedings of the 10th international conference on Intelligent user interfaces* (pp. 281–283). ACM.
- Sezgin, T. M., & Davis, R. (2008). Sketch recognition in interspersed drawings using time-based graphical models. *Computers & Graphics*, 32(5), 500–510.
- Tang, X., & Wang, X. (2004). Face Sketch Recognition. *IEEE Transactions on Circuits and Systems for Video Technology*, 14(1), 50–57.
- Walther, D. B., Chai, B., Caddigan, E., Beck, D. M., & Fei-Fei, L. (2011). Simple line drawings suffice for functional MRI decoding of natural scene categories. *Proceedings of the National Academy of Sciences of the United States of America*, 108(23), 9661–6.

Feature Evaluation for Discriminating Handwriting Fragments

Claudio DE STEFANO ^a, Francesco FONTANELLA ^a, Angelo MARCELLI ^b, Antonio PARZIALE ^b and
Alessandra SCOTTO di FRECA ^a

^a *Dipartimento di Ingegneria Elettrica e dell'Informazione
University of Cassino and Southern Lazio
Via Di Biasio, 43*

04303, Cassino (FR), ITALY

^b *Dipartimento di Ing. dell'Informazione, Ing. Elettrica e Matematica Applicata (DIEM)
University of Salerno
Via Ponte don Melillo, 1
84084, Fisciano (SA), ITALY*

(destefano, fontanella)@unicas.it, (amarcelli, anparziale)@unisa.it, a.scotto@unicas.it

Abstract. The large majority of methods proposed in literature for handwriting recognition assume that words are produced drawing large parts of the ink without lifting the pen, other than horizontal bars and dots. This fundamental assumption, however, does not always hold: while some educational systems provide explicit training for producing continuous handwriting, minimizing the number of pen-up during the production of a word, others do not. As a consequence, whenever the handwriting presents pen-up within a word, the recognition performance can drop significantly. In a preliminary study, we presented an algorithm for discriminating among different types of ink appearing in handwriting, namely isolated characters, cursive, dots, horizontal and vertical bars, based on the use of a suitable set of features. In this paper, we have characterized the discriminative power of each considered feature according to different measures and we have proposed a method for combining the different feature rankings. We have also used the Fischer's Linear Discriminant Analysis (LDA) for exhaustively selecting the best feature subsets with increasing number of features. Finally, we have compared the results obtained by using the feature subsets provided by LDA with those obtained with the feature subsets selected according to our feature ranking. The experimental results, on different datasets of handwritten words, showed that our approach successfully achieves its aim allowing to reduce the computational cost without affecting the overall performance of the recognition process.

1. Introduction

Handwriting generation studies, and more in general studies on motor control and trajectory planning, show that the complex movements involved in handwriting are composition of elementary movements, each corresponding to an elementary shape or stroke. Such strokes are drawn one after the other during handwriting and the fluency emerges from the time superimposition of them (Plamondon 1995, Grossberg & Paine 2000). Following this line of thought, we have conjectured that handwriting recognition can be achieved by providing the system with a *reference set*, i.e. a set of words whose transcripts are given, decomposing each of the reference word into strokes, and matching the strokes with the transcript so as to associate to each of them the ASCII code corresponding to the character the stroke belongs to. Once the reference set has been provided, handwriting recognition can be achieved by looking within the unknown word for sequences of strokes whose shape resembles that of sequences of strokes found in the reference set, labeling the sequence of the unknown as the matching ones in the reference set, and then combining the labels according to the writing order (De Stefano & al., 2010).

There are cases, however, when our conjecture does not hold. Those are the cases when the word is not produced by keeping the pen-tip in constant contact with the paper, so to have a continuous ink, but lifting the pen here and there while drawing. While such a habit is still within the domain of handwriting generation models, that can explain why and under which circumstances such a behavior appears, it may produce undesired effects in our prototype. Because of the pen lift, in fact, some of the movements do not produce an ink trace on the paper, and therefore some of the strokes are missed. So the sequence of strokes cannot be reconstructed completely, and some of the invariants may disappear, compromising the results of whole process.

To deal with those cases, we proposed in a preliminary study (De Stefano & al., 2011) a method for extracting from a word image the sub-images corresponding to pieces of ink produced without lifting the pen. Each sub-image was described by a suitable set of features and then classified as cursive, isolated character, vertical line, horizontal line, dot or noise. According to this approach, sub-images corresponding to cursive fragments can be processed as described before, while those containing characters can be passed to an OCR module. Thus, the recognition of the whole word can be obtained by composing the results of each module according to the position of the corresponding sub-images in the word image.

To better understand the effectiveness of the above approach, in this study we have characterized the discriminative power of each considered feature in classifying the pieces of ink produced without lifting the pen

as isolated characters or cursive. The basic motivation of our work is to answer this main question: “is it possible to describe handwriting movements just analyzing static images?” We will show that with a suitable set of features extracted from the original images it’s often possible to associate each pieces of ink to one of the above two classes.

The remainder of the paper is organized as follows: Section 2 describes the set of considered features, Section 3 illustrates the feature evaluation measures, while the analysis and the discussion of the experimental results, together with some concluding remarks, are eventually left to Section 4.

2. Feature description

The aim of the feature extraction process is that of allowing the classification of connected components of ink traces, possibly produced by writers without lifting the pen, in two main classes: isolated characters and cursive. The basic idea is that a simple shape is generated by a simple motor program. The simpler the motor program, the smaller the quantity of ink the connected component contains. However, in order to improve the fluency of handwriting, a writer may introduce extra strokes, or ligatures, to connect the last stroke of a character and the first of the following one, instead of lifting the pen between the final point of the former and the initial point of the latter. Accordingly, we expect that images of isolated characters will contain less ink (and less strokes) than those of cursive, and that the ink will not span prevalently along the writing direction (De Stefano & al., 2011)

In order to estimate the features of connected components of ink traces, we proceed as follows: The word image is processed for extracting the bounding box of each connected component (see Figure 1a). Then, each component is analyzed by considering its size, the number and the distribution of its black pixels and the size of the word it belongs to (see Figure 1b). In particular, we consider the coordinates of the top-left and bottom right vertices of the bounding box (X_{min} , Y_{min} , X_{max} , Y_{max}), the width and the height of the bounding box (W_{comp} , H_{comp}), the total number of pixels and the number of black pixels included in the bounding box (P_{comp} , BP_{comp}), the width and the height of the bounding box of the word (W_{word} , H_{word}).

Starting from these basic features, an additional set of features is computed, whose description is reported in Table 1. The features HR , AR and PAR are meant to capture the spatual, and hence the temporal, extension of the handwriting, while FF is meant to capture the spatial density of ink.

In order to evaluate the shape complexity of the ink trace, we have considered the number of transitions between white and black pixels along consecutive rows/columns of the component. These values have been arranged in two histograms, namely ink-mark on the horizontal (IM_x) and vertical (IM_y) axis, where each bin represents the above number of transitions for a group Δ along a row or a column, respectively (see Figure 1b). These features can be seen as a measurement of the complexity of the ink: an empty or flat ink-mark on both horizontal and vertical axis suggests that the component presents scattered black pixels and is likely to be noise, whereas higher values correspond to more complex shapes.

Finally, we have estimated the center-zone of the word and we have considered as features the y-coordinate of the upper side of the center-zone (say CZ_{Ymin}). Table 2 summarizes the whole set of considered features.

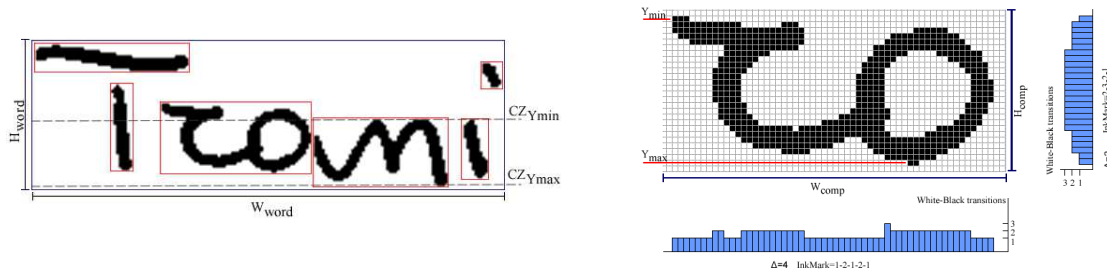


Figure 1: the image of word "Trani" with the bounding box of each connected component and the center zone; a connected component extracted from the word image (right).

Table 1: description of additional features

height ratio (HR)	aspect ratio (AR)	proportional aspect ratio (PAR)	fill factor (FF)
$HR = \frac{H_{comp}}{H_{word}}$	$AR = \frac{W_{comp}}{H_{comp}}$	$PAR = \frac{W_{comp}}{H_{word}}$	$FF = \frac{P_{comp}}{BP_{comp}}$

Table 2: the set of adopted features

F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12
IM_x	IM_y	X_{min}	Y_{max}	BP_{comp}	FF	AR	W_{word}	H_{word}	HR	PAR	CZ_{Ymin}

3. Feature evaluation

Two different approaches have been followed for evaluating the effectiveness of each feature and for identifying the subset of them having the highest discriminative power. The first approach is based on the use of standard univariate measures, while the second one uses the Fischer's Linear Discriminant Analysis (LDA).

In the first case, we have considered five standard univariate measures, where each of them ranks the available features depending on their ability in discriminating pieces of ink belonging to either isolated characters or cursive. In our study, we have considered the following univariate measures: Chi-square (*CS*) (Liu & Setiono, 1995), Relief (*R*) (Kononenko, 1994), Gain Ratio (*GR*), Information Gain (*IG*) and Symmetrical Uncertainty (*SU*) (Hall, 1999). The final ranking of all the features is computed by using the Borda Count rule, according to which, a feature receives a score that depends on its position in the rankings provided by each univariate measure. Once the final ranking has been obtained, subsets including increasing number of features (top1; top1 and top2; etc.) are used by a Support Vector Machine (SVM) classifier for testing their discriminating power.

The second approach for evaluating the behavior of subsets including increasing number of features is based on the use of the Fischer's Linear Discriminant Analysis (LDA). In this case we have exhaustively generated from the 12 available features, all the possible subsets of k distinct features, without repetitions, varying k from 1 to 12. Thus we created 4095 feature subsets, including 12 sets with only 1 feature, 66 sets with 2 features, 220 sets with 3 features, and so on up to the only set of 12 features. For each subset, the separation index S between the two classes has been computed. Denoting with 0 and 1 the two classes to be discriminated, S is defined as the ratio of the variance between classes to the variance within classes, using the mean vectors μ_0 , μ_1 and the covariance matrices Σ_0 , Σ_1 of class 0 and 1, respectively, and $\bar{\omega}$ is described in (De Stefano & al., 2014)

$$S = \frac{\sigma_{between}^2}{\sigma_{within}^2} = \frac{(\bar{\omega}(\bar{\mu}_1 - \bar{\mu}_0))^2}{\bar{\omega}^T (\Sigma_1 + \Sigma_0) \bar{\omega}}$$

The parameter S is a measure of how well the feature subset is able to discriminate between the two classes. It is worth noticing that S is a non-decreasing function with respect to the number of features included in a subset. This is the reason why we used S for ranking subsets including the same number of features. Once the best subset including k distinct features has been determined using the parameter S (with k ranging from 1 to 12), we used once again the SVM classifier for testing the discriminating power of that subset.

4. Experimental results

In order to ascertain the effectiveness of the proposed approach, two real world datasets involving handwritten words have been taken into account, namely RIMES and ELSAG database.

The RIMES database is a publicly available dataset used for performance evaluation of handwriting recognition systems (Grosicki, & 2008). It is composed of French words written by more than 1300 volunteers. To validate our algorithm, we extracted 4047 words from the test set and we showed them to 6 human experts. For each word, an expert had to classify manually each connected component and provide its transcript. At the end of this process, 9869 components were manually classified and transcribed, 5101 of them were cursive and 4768 isolated characters.

In the ELSAG database, a set of images representing postal addresses, acquired at 200/300 dpi, was processed in order to segment single words. Then, from each word, the connected components of ink traces, corresponding to cursive or isolated character, were extracted and described by using the above mentioned features. Moreover, in order to evaluate the classification results, each fragmented word image has been shown to 10 experts, and they were asked to label each fragment, to produce the ground truth. At the end of this process, a dataset of 26143 labeled samples has been obtained, containing 15838 isolated characters and 10305 cursive.

Feature evaluation based on the univariate measures has been applied to both databases, producing the results summarized in Table 3. Similarly, LDA approach produced the results reported in Figure 2, where the occurrence of each feature in the optimal subsets selected by LDA is shown. On the basis of these results and applying the previously discussed criteria, we obtained for both evaluation approaches, 12 subsets with increasing number of features, starting from the one including just 1 feature to that including all the 12 features. The effectiveness of each feature subset has been evaluated by implementing a SVM classifier using those features and measuring the recognition performance. In particular, we used for the SVM's the standard algorithm of regularized Support Vector Classification (C-SVC) with a Radial Basis Function kernel. The classification results reported in Figure 3 refer to the application of the 10-fold validation approach and show the plot of the recognition rate as a function of the number of features.

The analysis of these results confirms the effectiveness of the considered features, allowing us to obtain a maximum recognition rate equal to 92.55% and 93.65% for RIMES and for ELSAG database, respectively. The data in the plot show that satisfactory results can be obtained even considering only the top 3 features according

to the Borda Count overall ranking: in this case, in fact, a recognition rate of about 90% is obtained for RIMES database, while a recognition rate higher than 92% is obtained for ELSAG database. It is worth noticing that the results of the Borda Count are comparable, or in some cases better, than those obtained by the LDA. This aspect is particularly meaningful since the univariate measures combined by the Borda Count perform the feature ranking considering one feature at a time, while LDA performs an exhaustive search considering all the possible feature combination, thus implying a very high computational cost.

Future work will include exploiting the information about the classification reliability. Such kind of information would allow the designer of the system the implementation of a reject option for accepting only the high reliable classification on the basis of few features, thus limiting the use of more complex and computationally expensive feature only to the confused cases.

Table 3: Feature ranking according to the Borda Count overall measure. For each row, the leftmost value indicates the best feature, while the rightmost value denotes the worst one.

RIMES	F2	F8	F11	F7	F5	F1	F6	F9	F12	F10	F3	F4
ELSAG	F2	F8	F11	F5	F1	F7	F6	F10	F9	F4	F3	F12

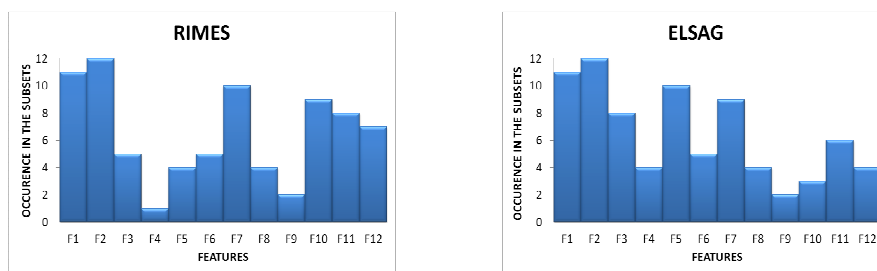


Figure 2: Occurrence of each feature in the optimal subsets selected by LDA for RIMES database (left) and ELSAG database (right).

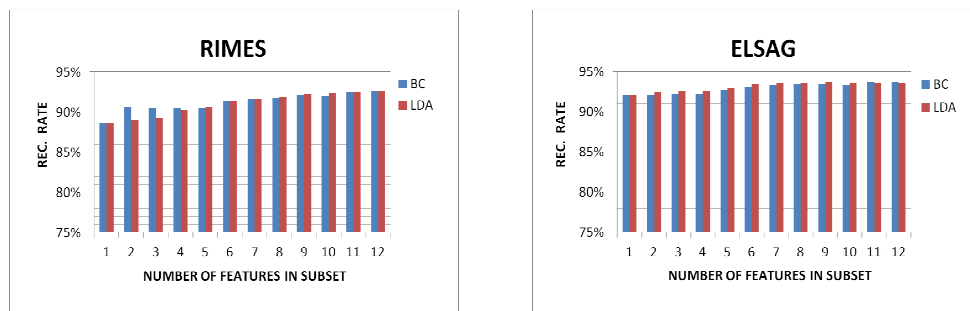


Figure 3: SVM classification results with 10 fold validation on features subsets for RIMES database (left) and for ELSAG database (right).

References

- Plamondon, R. (1995). A kinematic theory of rapid human movements. Part I: Movement representation and generation, *Biological Cybernetics*, 72, 297-307.
- Grossberg, S., & Paine, R.W. (2000). A neural model of corticocerebellar interactions during attentive imitation and predictive learning of sequential handwriting movements, *Neural Networks*, 13: 999-1046.
- De Stefano, C., Marcelli, A., Parziale, A., Senatore, R. (2010). Reading Cursive Handwriting, Proc. Int. Conf. on Frontiers in Handwriting Recognition - ICFHR 2010, Kolkata (INDIA), November 16-18, pp. 95-100.
- De Stefano, C., Marcelli, A. & Parziale, A. (2011). Segmenting Isolated Characters Within Cursive Words”, Proc. of the 15th International Graphonomics Society Conference (IGS 2011), Cancun, MEXICO, IGS press, pp. 156-159.
- De Stefano, C., Fontanella, F., Marrocco, C., Scotto di Freca, A., “GA-based feature selection approach with an application to handwritten character recognition”, *Pattern Recognition Letters*, Vol. 35, pp. 130-141.
- Liu, H. & Setiono, R. (1995). Chi2: Feature Selection and Discretization of Numeric Attributes. In: ICTAI, IEEE Computer Society, pp 88–91.
- Kononenko, I. (1994). Estimating Attributes: Analysis and Extensions of RELIEF. In: European Conference on Machine Learning, pp 171–182.
- Hall, M. (1999). Correlation-based Feature Selection for Machine Learning. PhD thesis, University of Waikato.
- Grosicki, E. & al. (2008). RIMES evaluation campaign for handwritten mail processing. Proc. of the Int. Conf. on Frontiers in Handwriting Recognition, Montreal, Canada, pp. 1- 6.

Predicting Hand Forces from Scalp Electroencephalography During Isometric Force Production and Object Grasping

Andrew PAEK^a, Pranav PARIKH^b, Alycia GAILEY^b, Marco SANTELLO^b, Jose CONTRERAS-VIDAL^a

^a *University of Houston, Department of Electrical and Computer Engineering,
4800 Calhoun Rd., N308 Engineering Building 1
77204, Houston, USA*

^b *Arizona State University, School of Biological and Health Systems Engineering
501 East Tyler Mall, ECG Building, Suite 334
85287-9709, Tempe, USA*

aypaek@uh.edu, Pranav.Parikh@asu.edu, agailey@asu.edu, marco.santello@asu.edu, jlcontr2@uh.edu

Abstract. In this study, we demonstrate the feasibility of predicting hand forces from brain activity recorded with scalp electroencephalography (EEG). Three able-bodied subjects participated in two tasks: an isometric force production task and a grasp-and-lift task using unconstrained and constrained grasps. We found that EEG electrodes spanning central areas of the scalp were highly correlated to force rate trajectories. Moreover, EEG grand averages in central sites resembled force rate trajectories as opposed to force trajectories. The grasp-and-lift task resulted in higher decoding accuracies than the isometric force production task: for each subject, median accuracies for the isometric force production task were $r=0.31$ and $r=0.43$ whereas median accuracies for unconstrained grasping were $r=0.61$ and $r=0.54$ and for constrained grasping were $r=0.55$ and $r=0.59$. Such results could lead to an understanding of the neural representation behind the control of hand forces and could be implemented in the neural control of closed-loop hand-based neuroprostheses.

Ortho-syllables and syllables affect the dynamics of adjective handwriting in French

Eric LAMBERT^a and Pauline QUEMART^a

^a *University of Poitiers - CNRS*

MSHS

5, rue Théodore Lefebvre

86000 Poitiers, FRANCE

eric.lambert@univ-poitiers.fr, pauline.quemart@univ-poitiers.fr

Abstract. Some research on written production has focused on the role of the syllable as a processing unit. However, the precise nature of this syllable unit has yet to be elucidated. The present study examined whether the nature of this processing unit is orthographic (i.e., the ortho-syllable) or phonological. Thirty-two native French speakers were asked to copy adjectives on a digitizer, successively adding a plural and a feminine one-letter morpheme to the same adjective. The adjective agreement could modify the structure of both phonological and orthographic syllables, only ortho-syllabic structure, or leave both unchanged. When the change modified only the orthographic syllable structure, there was an increase in duration at the letter before the syllable boundary. By contrast, when adding a letter changed both orthographic and phonological structures, an increase in the duration of the inter-letter interval was observed. Importantly, the increase in duration cannot be explained exclusively by the addition of a letter because the addition of a plural inflection did not significantly influence the dynamics of handwritten production. These results are consistent with the idea that ortho-syllables serve as a processing unit during handwriting, and that this type of syllable is specific to the written code.

1. Introduction

Although many studies have investigated the nature of the units involved in processing during language activities, very few have examined the nature and format of the units that are involved in the production of written words specifically. Some recent research suggests that the syllable may be one such processing unit. Research on handwriting dynamics in adults has revealed that word writing is regulated by syllable structure (Álvarez et al., 2009; Kandel et al., 2006; Kandel et al., 2011; Lambert et al., 2008; Sausset et al., 2012). Kandel et al. (2006) provided evidence that syllable boundaries within words modulate the timing of motor programming in the production of French and Spanish words. Movement durations – i.e., inter-letter intervals, such as the time period between the letters *a* and *c* in the French words *traceur* (“tracer”) and *tractus* (“tractus”) – are longer when the two letters occur at a syllable boundary (e.g., tra.ceur: syllable boundaries are indicated by a dot hereinafter) than when they belong to the same syllable (e.g., trac.tus). Similar syllable boundary effects have been found in word dictation and picture-naming tasks (Álvarez et al., 2009), and with keystroke intervals when typing in French (Zesiger et al., 1994), English (Kreiner, et al., 2008), Finnish (Service & Turpeinen, 2001), and German (Weingarten, et al., 2004). The impact of syllables on the dynamics of word writing has also been demonstrated by in analyses of writing latency (Lambert et al., 2008).

Although there is now a relative consensus on the role of the syllable in handwriting, the precise nature of this unit is still under debate. One view is that it is equivalent to the spoken syllable. This idea comes from phonological mediation view, according to which orthographic representations can only be accessed via prior retrieval of sound-based codes (Luria, 1970). According to this view, the processing units involved in the production of written syllables are the same as those involved in speech: letter chunks correspond to (phonological) syllables (Chetail & Mathey, 2010). An alternative approach suggests that written language production is relatively autonomous with respect to speech (Bonin, et al., 2001; Ward & Romani, 2000), and that the processing units involved in written language production do not derive exclusively from oral language.

Neuropsychologists were the first to introduce the concept of a unit which is similar to the syllable used in speech, but which based on graphemes, not phonemes: namely, the ortho-syllable (Caramazza & Miceli, 1990; Ward & Romani, 2000). In French, a mute *e* may affect the orthographic syllabification of a word and increase the number of syllables in the written form in comparison to speech segmentation. For example, the word *samedi* (“Saturday”) is a bi-syllable in speech (/sam.di/) but a three-syllable word in written language (sa.me.di). It thus provides a useful means for distinguishing between phonological and orthographic syllables. In this context, Lambert et al. (in press) asked French adults to copy three-syllable and two-syllable words with or without a mute *e* on a digitizer. In Experiment 1, the presence of a mute *e* in final position (e.g., *culture* vs. *coulour* vs. *cabinet*) increased writing latencies. In Experiment 2, which compared words with or without an internal mute *e* (*saleté* vs. *citron* vs. *salami*), latencies for three-syllable words (i.e., *salami*) did not differ from those for two-syllable words containing a schwa (i.e., *saleté*). However, writing latencies in these two conditions were longer

than for two-syllable words (i.e., *citron*). The results of the two experiments argue strongly in favour of a processing unit which is specific to written production, based on graphemic units rather than on phonological components such as spoken syllables.

Although they are very important, the results of Lambert et al. (in press) leave open the possibility that the activation of phonological representations is responsible for this effect. When processing words with an internal schwa (e.g., *saleté*) the participants might have first activated the phonological nucleus of the syllable (i.e., the mute e), which explains why such words are not processed differently from three-syllable words.

We thus sought to gather further evidence on the existence of orthosyllables in a new experiment. We asked undergraduate students to perform a copying task, in which they had to copy French adjectives on a digitizer. Their singular masculine form was presented on a computer screen (e.g., *noir*, “black”). Participants had to copy them first exactly and then with the addition, successively, of a plural and a feminine morpheme to the same adjective (e.g., *noir* – *noirs* – *noire*). Three different types of adjectives were used. In the first condition, feminine agreement did not modify the phonological or the orthographic syllable (e.g., *bleu* – *bleus* – *bleue*). In the second condition, feminine agreement changed the orthographic structure of the syllable but not the phonological structure (e.g., *noir* – *noirs* – *noire*). And finally, in the third condition, feminine agreement changed both the phonological and the orthographic structure of the syllable (e.g., *vert* – *verts* – *verte*). Note that in all three conditions, plural agreement requires the addition of a final -s but does not modify the phonological or orthographic structure of the syllable. Comparison of these three conditions will shed light on the type of unit (phonological syllable vs. orthosyllable) that is activated when handwriting.

2. Method

2.1 Participants. Thirty-two undergraduate students participated in the experiment. They were all native French speakers with normal or corrected-to-normal vision.

2.2 Material. The corpus consisted of a total of 36 adjectives that were divided into three conditions: 1) Feminine agreement did not change the syllabic structure of the adjective: e.g., BLEU /ble/ vs. BLEUE /ble/. 2) Feminine agreement changed the orthographic structure of the syllable only (e.g., NOIR /nwaR/ vs. NOIRE /nwaR/. 3) Feminine agreement changed both the phonological and orthographic structure of the syllable e.g., VERT /vèR/ vs. VERTE /vèR.t/.

2.3 Procedure. The experiment was run on a PC computer with a Wacom Intuos® 4 digitizer. Data were collected using the real time analysis software Eye and Pen© (Alamargot, et al., 2006). The adjective (in singular - masculine) appeared at the center of the screen, and the participants had to copy it in uppercase letters four times in a row (see Figure 1): 1) singular - masculine, 2) singular - feminine, 3) singular - masculine, 4) plural - masculine. All the conditions were counterbalanced across participants. Only the second, third and fourth copies were analyzed.

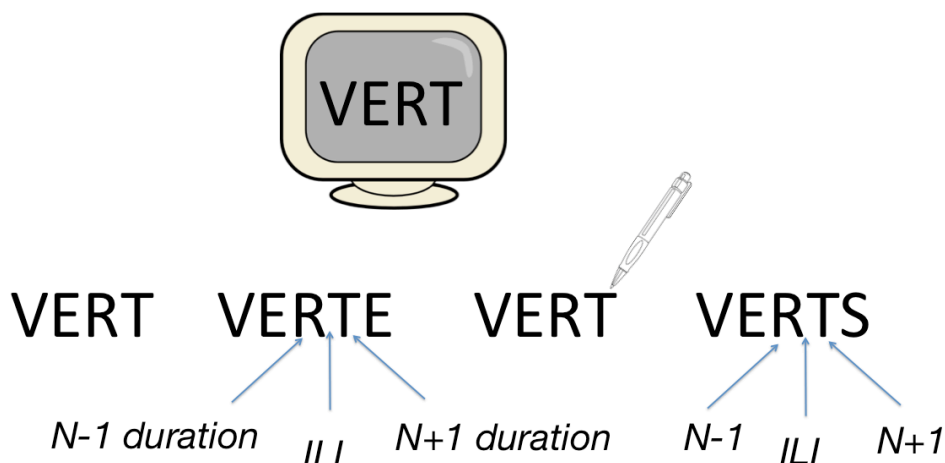


Figure 1. Each adjective was written four times: two times in masculine singular form, once in feminine singular form, and once in masculine plural form. The duration of the letter preceding (N-1) and following (N+1) the syllable boundary was analyzed, as well as the inter-letter interval (ILI)

2.4 Data analysis. Data were analyzed using a linear mixed-effect model with two fixed-effect factors (condition and type of agreement) and two random-effect factors (items and participants) for each dependent variable: letter duration before the syllabic boundary (N-1 duration), letter duration after the syllabic boundary (N+1 duration), and inter-letter interval (ILI).

3. Results and Discussion.

Table 1. Mean N-1 and N+1 durations and inter-letter interval (in ms)

Condition	Dependent variable	Masculine	Feminine	Plural
No change	N-1 duration	393 (138)	386 (153)	394 (146)
	N+1 duration	350 (194)	352 (191)	347 (176)
	ILI	144 (78)	154 (86)	152 (78)
Orthographic change	N-1 duration	295 (142)	317 (171)	299 (150)
	N+1 duration	399 (159)	378 (135)	392 (140)
	ILI	149 (72)	157 (71)	153 (65)
Orthographic and phonological change	N-1 duration	367 (138)	361 (153)	367 (146)
	N+1 duration	378 (122)	368 (85)	374 (93)
	ILI	147 (71)	168 (87)	152 (77)

In the condition with no change (Condition 1) there was no effect of the type of agreement (singular vs. masculine, feminine, plural) on the duration of the letter preceding the boundary, $F(2, 2461) = 1.19, p = .31$, the letter following the boundary, $F(2, 2461) = 0.27, p = .76$, or the ILI, $F(2, 2461) = 1.27, p = .28$.

In the condition with orthographic change only (Condition 2) there was no effect of the type of agreement on the ILI, $F(2, 2461) = 0.97, p = .38$, or on the letter following the boundary, $F(2, 2461) = 1.17, p = .31$. However, there was a significant effect of type of agreement on the letter preceding the boundary, $F(2, 2461) = 3.44, p = .032$. The mean production time of the letter preceding the boundary was longer when writing feminine adjectives (NOI.RE) than masculine adjectives (NOI.R), $t(2461) = 2.42, p = .016$, and plural adjectives, (NOI.RS), $t(2461) = 2.10, p = .036$. The two last conditions did not differ from each other, $t(2461) = 0.31, p = .75$.

In the condition with both phonological and orthographic change (Condition 3) there was no effect of the type of agreement on the letter preceding the boundary, $F(2, 2461) = 0.04, p = .97$, or on the letter following the boundary, $F(2, 2461) = 0.78, p = .46$. However, although there was also no significant effect of type of agreement on the ILI, $F(2, 2461) = 2.13, p < .12$, ILIs at the critical boundaries were longer for feminine adjectives (VER/TE) than for masculine adjectives (VER/T), $t(2461) = 2.00, p = .045$, or plural adjectives (VER/TS), $t(2461) = 1.97, p = .051$. The two last conditions did not differ from each other, $t(2461) = 0.56, p = .57$.

These results show that the impact of feminine agreement, with its addition of a mute e, on the dynamics of the handwritten production of adjectives depends on the type of syllabic modification created by letter addition. When the addition of a mute e changed only the orthographic syllable structure – NOIR vs. NOI.RE – there was an increase in duration at the letter before the syllable boundary. By contrast, when adding a letter changed both the orthographic and phonological structures – VERT /vèr/ vs. VER.TE /vèr.t/ – an increase in the duration of the inter-letter interval was observed. Finally, when adding a letter did not change the syllabic structure – BLEU / BLEUE – there was no effect of agreement. Importantly, the increase in duration cannot be explained simply by the addition of a letter, because the addition of a plural inflection did not significantly influence the dynamics of handwritten production: the difference between the masculine singular and masculine plural was never significant despite the addition of the plural marker –s. It is also important to note that the results are not related to letter differences (in terms of frequency or number of strokes for example): the letters compared were always exactly the same (eg. NOI.R / NOI.RE / NOI.RS).

These results are consistent with the idea that the ortho-syllable serves as a processing unit during handwriting, and that this type of syllable is specific to the written code. If the dynamics of handwriting were influenced by phonological representations, then we should have observed an impact of the addition of the feminine only when it modified the phonological syllable. To the contrary, our results show that the effect of the addition of the feminine is also significant when it affects only the orthographic syllable structure of the words. Thus, the modification of the syllabic structure by the addition of a feminine marker occurs at the orthographic level rather than at the phonological level.

Importantly, the addition of feminine agreement influenced handwriting dynamics at different points of word production. The effect occurs earlier when only orthographic structure is modified than when both orthographic and phonological structures are modified. This result might be explained by the greater complexity of the modification of the syllabic structure in the latter condition. This process is more complex and might therefore not be managed as early in processing. The modification of the syllabic structure involved in the

orthographic condition might be easier to process and thus be managed during the production of the letter preceding the boundary rather than afterward. More research is needed to further explore this issue.

The influence of phonological representations on written word writing is highly debated. According to the phonological mediation hypothesis (Luria, 1970), the activation of orthographic representations requires the activation of phonological representations. Evidence for such mediation has been found with a cross-modal repetition priming task: Participants were shown to systematically activate phonological representations (Damian et al., 2011). According to the orthographic autonomy hypothesis (Rapp et al., 1997), on the other hand, orthographic codes are activated directly from meaning, although phonological codes can also be activated in parallel. Our results are consistent with the existence of the ortho-syllable, and therefore favor the orthographic autonomy hypothesis. If orthographic processing occurs at least partly independently of phonological constraints, then this shows that orthographic codes can be activated directly from meaning. Further research is needed to establish a more precise model of the role of the ortho-syllable in handwriting.

References

- Alamargot, D., Chesnet, D., Dansac, C., & Ros, C. (2006). Eye and pen : a new device to study reading during writing. *Behavior Research Methods*, *38*, 287-299.
- Álvarez, C. J., Cottrell, D., & Afonso-Hernández, O. (2009). Writing dictated words and picture names: Syllabic boundaries affect execution in Spanish. *Applied Psycholinguistics*, *30*, 205–223.
- Bonin, P., Peereman, R., & Fayol, M. (2001). Do phonological codes constrain the selection of orthographic codes in written picture naming? *Journal of Memory and Language*, *45*, 688–720.
- Caramazza, A., & Miceli, G. (1990). The structure of graphemic representations. *Cognition*, *37*, 243-297.
- Chetail, F., & Mathey, S. (2010). InfoSyll: A syllabary providing statistical information on phonological and orthographic syllables. *Journal of Psycholinguistic Research*, *39*, 485-504.
- Damian, M. F., Dorjee, D., & Stadthagen-Gonzalez, H. (2011). Long-term repetition priming in spoken and written word production: Evidence for a contribution of phonology to handwriting. *Journal of Experimental Psychology : Learning, Memory & Cognition*, *37*, 813–826.
- Kandel, S., Álvarez, C., & Vallée, N. (2006). Syllables as processing units in handwriting production. *Journal of Experimental Psychology: Human Perception and Performance*, *32*, 18–31.
- Kandel, S., Hérault, L., Grosjacques, G., Lambert, E., & Fayol, M. (2009). Orthographic vs. phonologic syllables in handwriting production. *Cognition*, *110*, 440–444.
- Kandel, S., Peereman, R., Grosjacques, G., & Fayol, M. (2011). For a psycholinguistic model of handwriting production: Testing the syllable-bigram controversy. *Journal of Experimental Psychology: Human Perception and Performance*, *37*, 1310-1322.
- Kreiner, D. S., Zane Price, R., & Gross, A. M. (2008). Linguistic boundaries as predictors of the time between letters in oral and typed spellings. *The Journal of General Psychology*, *135*, 117-130.
- Lambert, E., Kandel, S., Fayol, M., & Espéret, E. (2008). The effect of the number of syllables on handwriting production. *Reading and Writing: An Interdisciplinary Journal*, *21*, 859–883.
- Lambert, E., Sausset, S., & Rigalleau, F. (in press). The ortho-syllable as a processing unit in handwriting: The mute e effect. *Reading and Writing: An Interdisciplinary Journal*, DOI: 10.1007/s11145-015-9545-4.
- Luria, A.R. (1970). *Traumatic aphasia*. The Hague, The Netherlands: Mouton.
- Rapp, B., Benzing, L., & Caramazza, A. (1997). The autonomy of lexical orthography. *Cognitive Neuropsychology*, *14*, 71–104.
- Sausset, S., Lambert, E., Olive, T., & Larocque, D. (2012). Processing of syllables during handwriting: Effects of graphomotor constraints. *Quarterly Journal of Experimental Psychology*, *65*, 1872–1879.
- Service, E., & Turpeinen, R. (2001). Working memory in spelling: Evidence from backward typing. *Memory*, *9*, 395–421.
- Ward, J., & Romani, C. (2000). Consonant-vowel encoding and orthosyllables in a case of acquired dysgraphia. *Cognitive Neuropsychology*, *17*, 641–63.
- Weingarten, R., Nottbusch, G., & Will, U. (2004). Morphemes, syllables and graphemes in written word production. In T. Pechmann & C. Habel (Eds.), *Multidisciplinary approaches to language production* (pp. 529-572). Berlin, Germany: Mouton de Gruyter.
- Zesiger, P., Orliaguet, J. P., Boë, L. J., & Mounoud, P. (1994). The influence of syllabic structure in handwriting and typing production. In C. Faure, G. Lorette, & A. Vinter (Eds.), *Advances in handwriting and drawing: A multidisciplinary approach* (pp. 389–401). Paris, France: Europa.

How Handwriting Evolves: An Initial Quantitative Analysis of the Development of Indic Scripts

Vinodh RAJAN
School of Computer Science, University of St Andrews
KY16 9SX, St Andrews, SCOTLAND
vrs3@st-andrews.ac.uk

Abstract. Indic scripts are among few scripts in the world that have had continuous development for more than two millennia. The modern forms of the scripts are the result of infinitesimal changes in handwriting being accumulated over centuries. They present us with a unique opportunity to understand various changes occurring in handwriting behavior. We have taken four major Indic scripts in six different stages of evolution and extracted features quantifying their handwriting behavior. We have derived these features by applying the principles of handwriting production and gesture analysis on a paleographic data set. We present various trends and behaviors that occurred during script development and discuss our interpretation of the results in terms of evolution of handwriting behavior. We then briefly discuss the detailed analyses that will be performed on the dataset in the future. We also consider the applications of these results in digital paleography and handwriting-driven systems.

1. Introduction

The myriad of modern Indian scripts that exist today were all derived from the same source script i.e. Brahmi. There have been several competing theories about the origins of Brahmi itself, but the general consensus is that it was largely inspired or derived from the Aramaic script (Salomon, 1998). Probably due to partial constructed nature, the initial shape of the Brahmi script was largely geometrical, but it has given rise to a wide variety of scripts over time due to inherent variations in human handwriting. Indic scripts are among the few script families around the world that have existed as a continuum for several centuries. Hence, for any Indic script, we can derive an “almost” linear evolutionary line from Brahmi. Therefore, we have a unique opportunity to analyze script developments in terms of changes in handwriting behavior. We can investigate how the different handwriting features have evolved in terms of handwriting production and visual appearance. This will also enable us to understand the variations in handwriting that occur due to the complex interplay of different features.

2. Data Set

To obtain a comprehensive view of the script development process we have taken four major scripts belonging to the Brahmic family – Devanagari, Tamil, Kannada and Grantha. These scripts represent most of the important Brahmic scripts in India. We consider the scripts in six stages of evolution. A single stage of a script can be considered to represent ~300 years covering ~1800 years of development. It is to be noted that the scripts themselves show large geographical and scribal variations even over the same time period. Ojha (1959) had presented the development of the scripts by normalizing the shapes, which is utilized by us. However, some characters have had fewer distinct variations compared to others. In such cases we have normalized the number of characters in each script by carrying over the stabilized characters to subsequent developments. We have also considered only glyphs that have had consistent development from Brahmi and ignored secondary developments that have occurred later (such as characters getting derived from other characters using diacritical signs). Grantha, Devanagari and Kannada have ~40 characters each in their repertoire while Tamil has ~20 characters. In total, we have 20 (4×5) distinct stages consisting of ~730 distinct glyphs with Brahmi as the source script. (All four scripts share Brahmi as their initial form.)

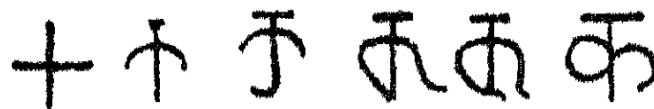


Figure 1. Devanagari Character KA in six different stages of development (Ojha, 1959)

3. Data Extraction

The scripts were digitized using the script analysis framework that was proposed in Rajan (2014a). Characters were first converted into splines, followed by reconstruction of their trajectories and then finally decomposed into their respective strokes. At the end of the process we had the stroke structure of the characters digitized and ready for feature extraction. Rajan (2014b) also proposed a set of objective features that quantify various aspects

of handwriting. From this normalized stroke structure we extract two types of features, geometric features and production features, which were used for subsequent quantitative analyses. The geometric features consisted of 9 different features based on the static shape of characters and the production features consisted of 12 different features based on the written trajectories.



Figure 2. Script Repository

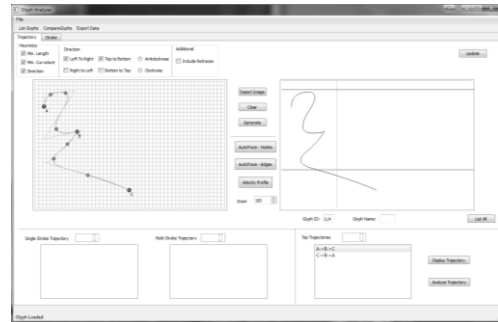


Figure 3. Digitized Character



Figure 4. Decomposed Character

4. Trends in Features

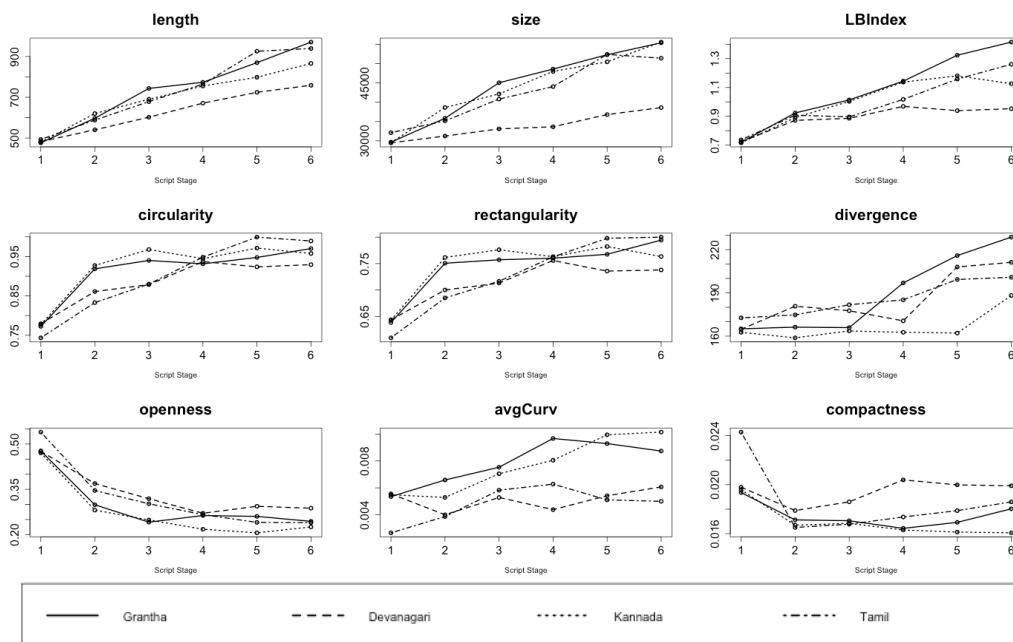


Figure 5. Trends in geometric features

Figure 5 shows the general trend in the averages of various geometric features of scripts across the timescale of development. We can see that the *size* and *length* of the glyphs steadily increased over time. Also, the *LBIndex* (the ratio of *width* & *length*) indicates that the glyphs were becoming more and more wide. The outline shapes of the glyphs approached an ideal geometric shape as noted by the increase in *circularity* and *rectangularity*. This may be ascribed to the latent human nature to idealize the overall glyph outlines into symmetric shapes. In terms of pen positions, *divergence* (the difference between starting and ending position of

the pen) increased over time. This appears to be a consequence of a corresponding increase in length of characters. As a result, it would take more effort to maintain the starting and ending positions of the writing instrument near each other. With respect to total length, however the pen positions became closer as shown by the decrease in *openness* (the ratio of *divergence* to *length*). *Compactness* (the ratio of *length* and *area*) also appears to have dropped significantly. Brahmi had more strokes constricted into the same area with scribes further spreading out the strokes. In terms of curvature, the latent trend is towards highly curved glyphs. This is understandable, as it has been suggested that it is easier for humans to produce curved segments as compared to straight lines (Altmann et al., 2008), because the latter requires more effort.

To summarize, in terms of the geometric appearance, the general trend appears to be towards “long”, “large”, “symmetric”, “divergent”, “wide”, “curved”, “closed” and “loose” glyphs.

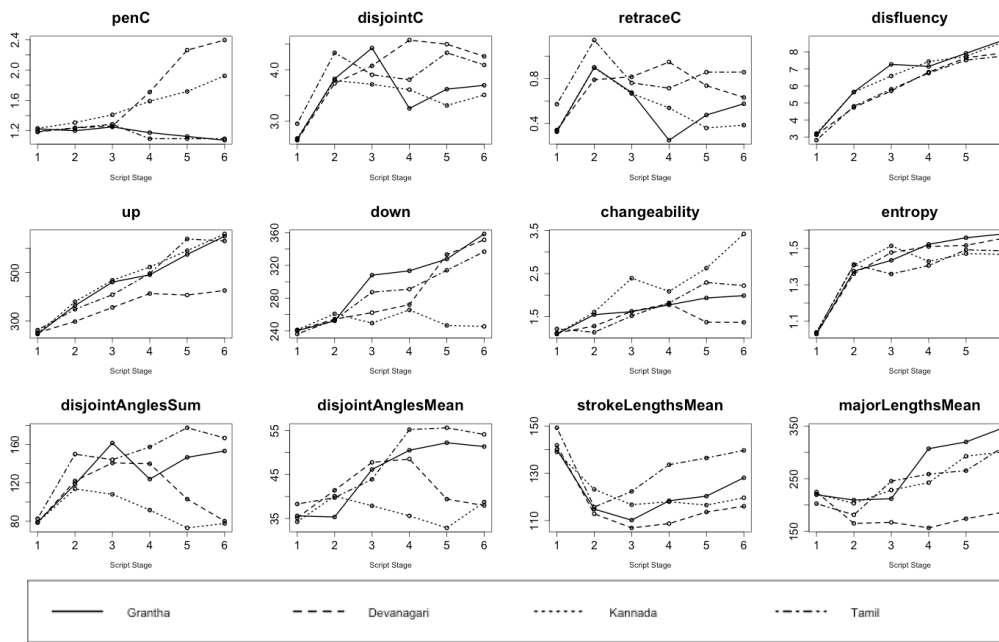


Figure 6. Trends in production features

Figure 6 shows the general trends for the production features. The split in *pen count* is due to the fact that Devanagari and Kannada developed an additional pen stroke uniformly in all characters. If this is factored in, all the scripts have maintained their characters as effectively requiring a single pen stroke. The average *disjoint count* (strokes with sharp velocity break during handwriting production), though seen to be increasing, apparently bounds itself, fluctuating between 3.5 and 4.5. This is slightly higher than the proposed average stroke count of three by Changizi et al. (2005). There also seems to be some fluctuation in retraces but at the end it averages to one retrace per character. In terms of the length of *upstrokes* and *downstrokes*, it again shows a uniform increase as one would expect based on the increase in the *length* and *size* of the characters in Figure 5. Also, Brahmi starts with very low stroke *changeability* but as scripts developed it increased. This appears to contradict the initial diversification of scripts. (*Changeability* here refers to the ratio of up and down strokes and hence implies changes in glyphs occurring due to the instability of fundamental strokes, since up strokes are less stable than down strokes (Teulings et al., 1993)). We can assume that such instability effectively contributed the least (if at all) to the diversification, with other factors probably contributing more. *Entropy* of writing is also shown to be increasing but tending to reach a limit ultimately. In terms of stroke features, length of basic strokes fell initially and then showed a slow growth. In terms of complex strokes (major strokes), there is a more or less uniform increase. In terms of stroke angles, there seem to be a general increase in angles with both the mean and the sum corresponding to the increase in *disfluency*.

In Figure 5 and Figure 6 we can see that many features show logarithmic or “near” logarithmic growth with *compactness* and *openness* showing a negative logarithmic growth. Most of these are major features that define handwriting behavior. This shows that characters after an initial period of diversification began to stabilize slowly. Explicit logarithmic growth is seen in cognitively related features like *disfluency* and *entropy*, which we consider as significant.

One would expect that humans tend to reduce *disfluency* to increase writing speed but on a large scale it appears not to be the case. Writing appears to have gathered more *disfluency*, more *disjoint strokes* and a

corresponding increase in *entropy*. As discussed earlier, in terms of static features, characters have also gained *length* and *size* as time progressed. It also points to the fact that characters show a logarithmic increase in *complexity* in terms of production and appearance, which is counter-intuitive. Our interpretation is that this is due to “*information*” being continuously added albeit in minute amounts in terms of production and static appearance. In the end this resulted in complex glyphs that had resulted from what started out as simple geometric figures. But the logarithmic profile of many features points to the fact that the rate of new *information* being injected into the characters slows down after some time and scripts tend towards stability.

5. Diversifying Features

Discriminant analysis is a frequently used multivariate statistical technique to find aggregate variables that best discriminate groups in a given set of data. This technique when applied to the entire script development data results in discriminants that identify/label characters as belonging to a particular script. These discriminants can be interpreted as the major factors on the basis of which different scripts are identified and differentiated. Consequently, in terms of script development these can be further elaborated as the factors, which caused diversification. The analysis was performed separately with geometric and production features.

Table 1. Coefficients of geometric linear discriminants

<i>Features</i>	LD^G_1	LD^G_2
Length	-0.00059865341	0.007731254
Size	0.00009528834	-0.000115424
LBIndex	1.28843838989	0.186680755
Circularity	-3.48149787949	8.526610933
Rectangularity	8.27051387586	-14.373985382
Divergence	-0.00159561490	0.008506504
Openness	-0.06621315085	0.124090255
Avg. Curvature	9.73404814509	-27.513799916
Compactness	34.75293555964	-30.978259631

With geometric features, we find that the first two linear discriminants - LD^G_1 and LD^G_2 - contribute up to ~85% of the discriminatory power. LD^G_1 discriminates scripts using mostly *compactness* with minor contributions from *average curvature* and *rectangularity*. LD^G_2 on the other hand discriminates based on nearly equal contribution from *average curvature* and *compactness* and significant contribution from *rectangularity* and *circularity*. It follows that scripts have diversified based on the following major geometric features - *compactness*, *average curvature*, *circularity* and *rectangularity*. Characters’ curvature and their shape outlines have together played a major role in diversification. However, the fact that *compactness* has turned out to be a major factor that determines a script is rather surprising. If we consider *compactness* as related to the arrangement of strokes in a character, it is indeed one of the diversifying factors during script development.

Table 2. Coefficients of productive linear discriminants

<i>Features</i>	LD^P_1	LD^P_2
Pen Count	0.0739570676	-1.2215776695
Disjoint Count	-0.4456953605	-0.2275291566
Retrace Count	-0.2803731156	-0.1119661255
Disfluency	0.0325610130	0.0350712045
Up Strokes	0.0066029962	-0.0001094251
Down Strokes	0.0035771170	-0.0018496560
Changeability	0.0785589768	-0.1844057565
Entropy	-0.3723920326	-0.7759867001
Sum of Disjoint Angles	0.0043322933	0.0084563084
Mean of Disjoint Angles	0.0019477094	-0.0061158837
Mean of Fundamental Stroke Lengths	-0.0047329371	0.0035754377
Mean of Major Strokes Lengths	-0.0000481335	0.0003249647

With production features, we find that the first two linear discriminants – LD^P_1 and LD^P_2 – contribute up to ~72% of the discriminatory power. Though this is not very high compared to the geometric features, it is still a reasonable amount of cumulative discrimination. LD^P_1 classifies characters mainly based on *entropy*, *retrace count* and *disjoint count* with minor contributions from *pen count* and *changeability*. LD^P_2 classifies mostly based on *entropy* and *pen count* with significant contributions from *disjoint count* and *retrace count*. With

production characteristics, scripts have diversified mostly based on *entropy* of writing and the number of major strokes in characters contained in a script.

6. Spread of Variations in Characters

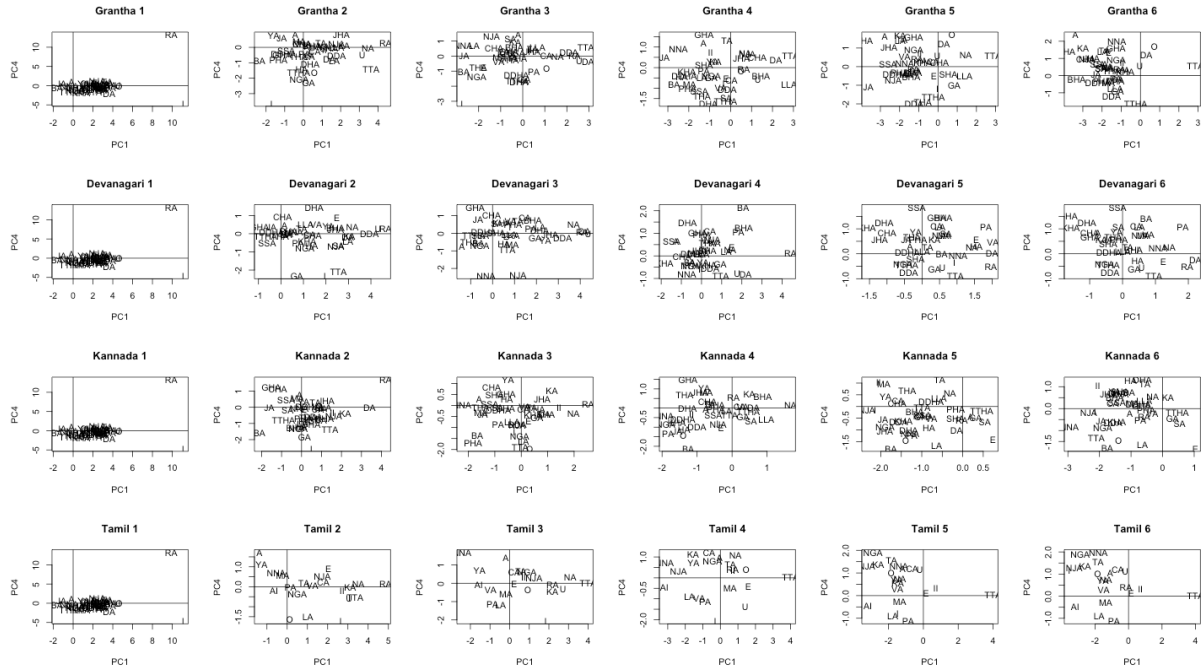


Figure 7. Plot of PC1 vs PC4 for scripts in all 6 stages of development. The labels for the data points refer to the Unicode name of the characters.

In section 4, we discussed the general trends in various features of scripts during the script development process. In this section, we analyze the individual character variations that occurred. The original feature set consisting of 9+12 features is too large for individual character-wise analysis. Hence, we proceeded to perform Principal Component Analysis (PCA), which reduced the feature set and also resulted in descriptive aggregate features.

Table 3. Loadings of Principal Components

Features	PC1	PC2	PC3	PC4
Length	-0.476	0.183		0.449
Size	-0.324	0.493	-0.300	0.171
LBIndex	-0.244	0.253	0.299	
Circularity	-0.478	-0.245	0.274	-0.246
Rectangularity	-0.463	-0.269	0.348	-0.237
Divergence		0.485	0.512	0.230
Openness	0.350	0.256	0.526	-0.139
Avg. Curvature	-0.204	0.261	-0.131	-0.473
Compactness		-0.399	0.244	0.597

Table 3 shows the first four principal components derived by applying PCA to geometric features in the dataset. The shown principal components account for nearly 78% of all variance in the dataset and hence are sufficient to abstract the multivariate dataset. PC1 is a comparison between *openness* and mainly *circularity*, *rectangularity*, and *length*. Characters that are “open”, “short” and “asymmetric” have positive scores, while “closed”, “long” and “symmetric” characters will have large negative scores. PC2 compares *compactness*, *circularity* and *rectangularity* with mostly *size* and *divergence*. Characters with negative PC2 scores are typically “compact” and very “symmetric”. Positive scores indicate characters that are “large” “loose” “divergent”. For PC3, high negative scores indicate “large” and highly “curved” characters. For PC4, large negative scores point to highly “curved” and “symmetric” characters with positive scores pointing to characters that lack those characteristics.

We specifically discuss the plots of PC1 vs PC4 for illustration. It can be clearly seen from Figure 7 that Brahmi characters had very similar geometric profiles initially (evident by the crowded overlap of characters). But as time passed by, the characters did diverge significantly as discussed earlier. Here we can see a particular pattern in the diversification process. In Brahmi, the characters are primarily around the first and fourth quadrant boundary. The characters are just “open” “short” and “asymmetric” During the second stage of diversification characters gain more “symmetry” “closure” and “length” moving towards other quadrants but mostly dispersing towards the first and third quadrants with ultimately many of the characters moving into the second and third quadrants thus gaining “curved symmetry” along with “lengthy closure”. We can clearly see the interplay of features that cause the variations.

Other principal components were also compared to derive information on other aspects of variations that occurred. We performed similar analysis on the production features.

6. Future Work

The nature of distribution of features and their corresponding changes are very interesting phenomena, which needs to be analyzed. The influence of usage frequency on character properties is also to be studied in detail. We are currently analyzing the change in stroke inventory and their impacts on character self-similarity within the scripts. We also plan to extract specific feature sets that have produced fairly stable characters. The very important interaction between the geometric and production features behavior is to be studied in the future.

7. Applications

Paleography has mostly been a subjective field. The quantitative techniques and feature sets used by us contribute towards a more objective and quantitative paleographic analysis. Although, the results presented here are specific to Indic scripts, the techniques can be duplicated and expanded for other kinds of paleographic scripts. Findings from paleography can also be applied to Human-Computer Interaction. If Brahmi is considered as an archetypical “constructed” set, many of the results presented here (and the results of our future work) can be used to construct “optimal” gesture sets. Learning from such paleographic patterns and behavior, we can attempt to construct gesture sets that are *natural, easy to use and stable*.

7. Conclusion

We have presented our initial quantitative analysis of the development of Indic scripts using Devanagari, Kannada, Tamil and Grantha as archetypes. We have presented the general trends in handwriting that occurred during script development and our analysis and interpretation of those trends. We also found the major features on the basis of which the scripts diversified over the years. Additionally, we analyzed the variations acquired by individual characters using aggregate features. We briefly discussed future work and possible practical applications of this analysis in the fields of Digital Paleography and HCI.

References

- Altmann, G., and Fan F. (2008). (Eds.). Analyses of script: properties of characters and writing systems. Vol. 63. Walter de Gruyter. APA
- Changizi, M. A., and Shimojo, S. (2005). Character complexity and redundancy in writing systems over human history. Proceedings of the Royal Society B: Biological Sciences, 272(1560): 267-275.
- Ojha, G. H. (1959). Bharatiya Prachina Lipimala. New Delhi
- Rajan, V. (2014a). Framework for Quantitative Analysis of Scripts. Proceedings of Digital Humanities, DH 2014.
- Rajan, V. (2014b). Quantifying Scripts: Defining metrics of characters for quantitative and descriptive analysis [Manuscript submitted for publication, arXiv:1501.01894]
- Salomon, R. (1998). Indian Epigraphy. A Guide to the Study of Inscriptions in Sanskrit, Prakrit, and the Other Indo-Aryan Languages.
- Teulings, H. L., and Schomaker, L. R. (1993). Invariant properties between stroke features in handwriting. Acta psychologica, 82(1): 69-88.

An algorithm based on visual perception for handwriting comparison

Antonio Parziale, Stanislao Davino and Angelo Marcelli

*Natural Computation Lab,
Department of Information Engineering, Electrical Engineering and Applied Mathematics
University of Salerno
Via Giovanni Paolo II, 132
84084, Fisciano (SA), ITALY*

Abstract. We propose an algorithm based on a model of visual perception that is meant to reflect the human judgment about the similarity of handwritten samples. The algorithm builds upon the Fuzzy Feature Contrast model and proposes an implementation of such a model in the domain of handwriting. The algorithm has been validated on the RIMES dataset, by comparing its performance with those of a panel of human experts. The experimental results show that the performance of the proposed algorithm is almost indistinguishable from the expert one and therefore may be a viable tool for handwriting comparison.

1. Introduction

Human perception of shape similarity has been the subject of many studies in diverse fields, such as experimental psychology, neuroscience, visual perception and artificial intelligence, just to mention a few. In such a context, the similarity/dissimilarity between stimuli seems to play a key role in defining the categories the organism needs to properly behave in an ever-changing environment. A concise yet comprehensive survey of the current opinions on the subject from such a point of view may be found in (Blough, 2001).

In the realm of handwriting analysis and recognition, when dealing with the problem of building a machine capable of comparing the shape of handwriting sample, the usual assumption is that the similarity of the samples is reflected by the distance of their representations in a feature space: the closer the representations are, the more similar the samples are. The approach makes two fundamental assumptions: the samples can be represented by values of a few distinctive characteristics, or features, and their distance in the feature space reflects their similarity (Plamondon & Srihari, 2000). Although this approach has led to applications for handwriting analysis and recognition that are routinely used, such as signature verification, OCR, postal address recognition and check processing, in case of cursive handwriting it provides solutions that are in contrast with the results of experiments with human beings. The book by Pekalska and Duin discusses the limitations of such an approach, argues that the notion of similarity is more fundamental than that of a feature or a class, introduces similarity representations and methodologies to deal with them (Pekalska & Duin, 2005).

Among the theoretical approaches to similarity, the *Feature Contrast model* originally introduced by Tversky accounts for several characteristics of similarity data that contradict the metric assumption discussed above, mainly asymmetry and angular inequality (Tversky, 1977). The model, however, assumes that each sample is described by a binary vector, each element of which represents whether or not the corresponding features is present in the sample. Santini and Jain have extended the original model into the *Fuzzy Features Contrast model*, by proposing to represent the sample by a fuzzy feature vector, each element of which represents the fuzziness of the presence of the corresponding features in that sample, thus allowing to deal with cases when features enumeration is either impractical or impossible (Santini & Jain, 1999).

Along this line of investigation, and assuming that cursive handwriting is a sequence of strokes as suggested by many studies on handwriting generation, in Section 2 we propose an implementation of the Fuzzy Feature Contrast model for cursive handwriting that builds upon a novel set of features to describe both the shapes and the spatial arrangement of the strokes, and an algorithm for evaluating the similarity between two cursive fragments. In Section 3 we present the results of two experiments performed to validate the model and to assess its performance. Eventually, we discuss the experimental results and outline possible directions for future investigations.

2. Ink Similarity

Most of the features used by the Ink Similarity algorithm are based upon measures and classification related to single strokes. The Fuzzy Feature Contrast Model assumes that the feature vectors of the two stimuli have the same dimension; for this reason, to generate “global” features vectors of the same dimension starting from “local” features vectors of different dimension, we decide to aggregate “local” strokes information to obtain “global” information. For each handwritten fragment image, the algorithm creates a vector of 54 elements that holds 3 different types of features: *Zone*, *Curvature* and *Shape* features, as described below.

2.1 Zone features

The sequence of strokes extracted from the ink is preliminarily partitioned in three subsequences: the first one containing the strokes that span over the first 30% of the horizontal size of the word, the second containing the strokes that span over the following 40% of the word, and the third containing the remaining strokes. Each stroke is then classified depending on which part of the word layout it occupies. A zoning algorithm, based on the histogram of the horizontal projection, evaluates the size of the center, the bottom and the upper zones of the word layout. We have defined 15 zone features for each stroke, depending on the position of the stroke in the zone and the way they are drawn: Ascender (Up/Down), Descender (Down/up), Upper (Center/Bottom/Top), Lower (Center/Top/Bottom), Center (Center/Upper/Lower), Pipe and Loop. As each features is evaluated for the three subsequences, we have 45 zone features in total. Fig. 1a) shows the features from left to right, and Fig. 1b) the partition of the sequence of strokes of the word “est” and the zones detected by the zoning algorithm. For each of them, the Ink Similarity counts how many times the i -th zone feature appears in the sequence, and then calculate the ratio between such a count and the total number of strokes. This number is then used as a *crisp* value of a linear membership function to obtain the fuzzy value.

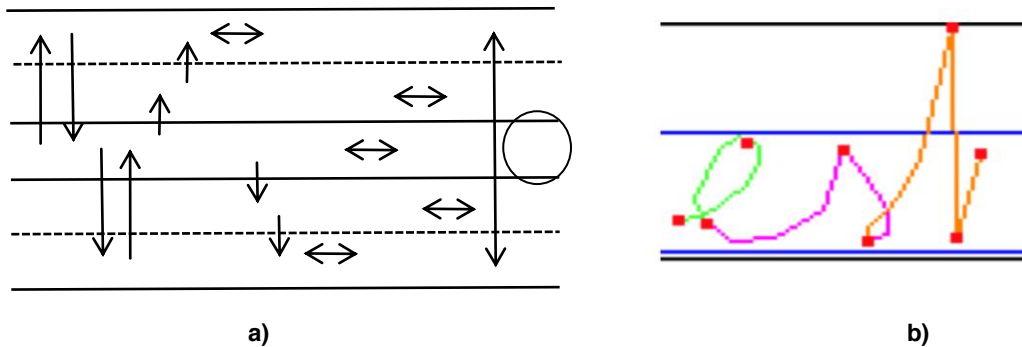


Figure 1 The “zone” features. a) The features: their labels depend on both the writing direction (represented by the arrow) and the zones of the stroke extremes. The arrows are not representative of the actual shape of the strokes. b) the partitioning into subsequences: begin (green), middle (magenta) and end (yellow)

2.2 Curvature features

As in the zone features case, the curvature features are extracted from subsequences of the sequence of strokes extracted from the ink, but in this case there are five subsequence, each one containing the strokes that span over the 20% of the word horizontal size, from the beginning to the end. For each subsequence we compute the average of the curvature maxima of the strokes, obtaining 5 curvature features. Such a count, normalized as above, is then used as *crisp* value of a linear membership function.

2.3 Shape features

In contrast to the previous ones, shape features do not build up on stroke features, but have the purpose of describing the entire shape of the word. We adopted the 4 word features proposed in (Powalka & al, 1997): Middle, Middle-Upper, Middle-Lower and Upper-Middle-Lower. From the output of the zoning algorithm, and for each word feature, we compute two parameters: the vertical size of the center zone, ($Width$) and the distance between the middle line of the center zone and the bottom line of the bottom zone ($YPos$). Their values are then used as *crisp* value for two membership functions, $F_{YPos}(YPos)$ and $F_{Width}(Width)$ as in fig. 2, whose outputs are eventually combined to obtain the feature score as $\min(F_{YPos}(YPos), F_{Width}(Width))$. Eventually, from each score, the degree of ownership of the word’s shape features is computed by means of a linear membership function.

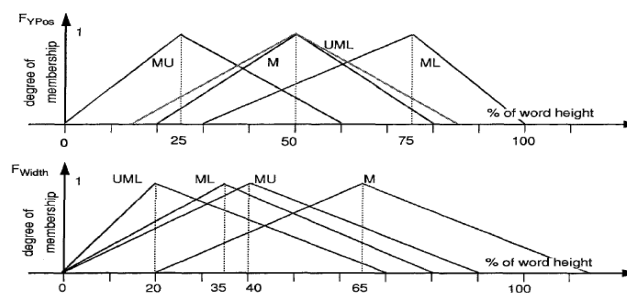


Figure 2. The membership function for the shape features.

2.4 Similarity measure

Given two handwritten words, each one represented by the feature vector described above, we assume as similarity measure between them the following:

$$S(a,b) = \frac{f(A \cap B)}{f(A \cap B) + \alpha f(A - B) + \beta f(B - A)}$$

where:

- a and b represent the image of two cursive handwritten words;
- A and B represent the fuzzy features vectors associated to a and b as described before;
- $A \cap B$ represents the intersection between the two fuzzy vectors. The resulting vector represents the common features between a and b ;
- $A - B$ and $B - A$ represent the complements between A and B . The resulting vectors represent the distinct features between a and b ;
- $f(FV)$ is the saliency function that associates to an entire feature vector FV a single number; in our implementation we choose the function f as: $f(FV) = \sum_{i=1}^{54} FV_i$
- α and β are two weights that model the imbalance of the judgment of inequality that is typical of human judgment.

3. Experimental results

In order to validate the proposed model, we have performed a set of experiments on the RIMES dataset, a publicly available dataset largely used for performance evaluation of handwriting analysis and recognition systems (Grosicki & al., 2008). From the data set, we have selected 10 images of the bigram “en” and 10 images of the word “es” as Reference Set (RS) and again 10 images of the bigram “en” and 10 images of the bigram “es”, different from the previous ones, as Test Set (TS).

In each experiment, 1 image of TS and 5 images of RS, randomly selected but the same for all the subjects, were shown to each subject, and he/she was asked to rate the similarity between the Test image and each of the Reference one. The rating was reported by using a 5-point scale, ranging from 1, the most similar, to 5, the least similar. Figure 3 shows the GUI designed for the experiments with the human subjects. The same task was assigned to the algorithm, so as to have, for each image of TS, the ranks of 17 subjects and the rank of the algorithm.

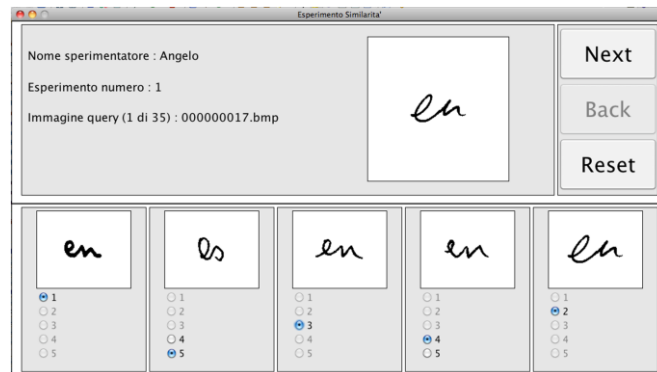


Figure 3. The GUI used during the experiments. The subjects were requested to rank the similarity between each of the Reference images shown in the bottom pane with the Test image shown on the top pane by using a 5 point scale, with 1 representing the most similar Reference image and 5 the least similar one.

Then, for each image of TS, we measure the difference D in the ranks by the formula:

$$D = \sum_{i=1}^5 d_i * w_i$$

where d_i is the difference between the position of the i -th image of RS in the two ranks and $w_i = 1$ for the top/bottom position of the rank, 0.5 for the following/preceding one and 0.25 for the middle position. The weights have been fixed so as to ensure that very similar/dissimilar feature plays a major role in the final judgment, as in the case of human perception of similarity. Figure 4a) reports the level of agreement between the

subjects for 10 of the images of TS, while figure 4b) reports, for the same images, the value of D between the rank provided by the proposed algorithm and the one obtained by combining the ranks of the subjects by the Borda count method (deBorda, 1781), as to represent the “mean” behavior of the human subjects.

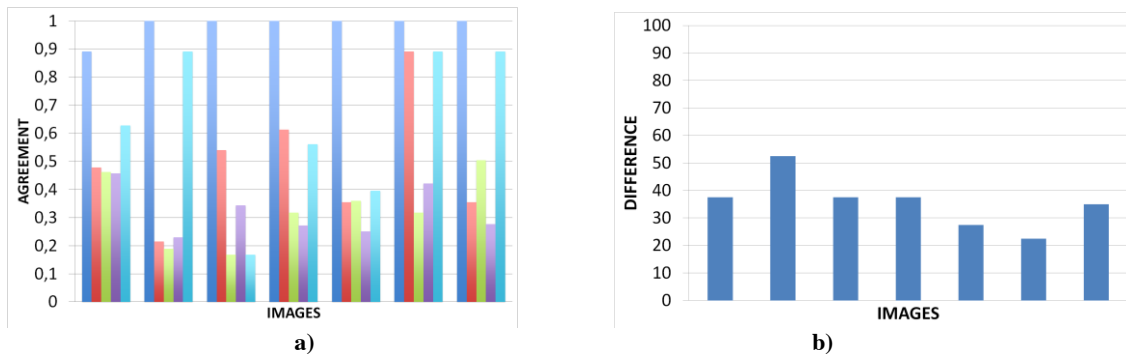


Figure 3. The experimental results: a) the agreement on the ranking between the subjects: each of the 5 bars refers to the agreement on the corresponding position of the rank; b) the difference between the algorithm and the “mean” subject. For sake of legibility, the figure reports the results on a few images selected as representative of the performance on the whole Test set.

Conclusions

We have presented an algorithm to evaluate the similarity between handwritten words that builds upon a fuzzy computational model proposed to account for the visual perception of similarity. Such a general model has been customized by adopting a suitable set of features to represent the distinctive feature of handwriting and its performance compared with that of human subject in a similarity evaluation task.

The experimental results allow for the following preliminary conclusions:

- the ranks of the human subjects are more similar as with regards to the most/least similar shapes than with regards the shapes that are somehow in between these extreme cases;
- the difference between the rank of the algorithm and those of the subjects may vary, but even in the worst case such a difference is slightly bigger than 0.5, meaning that at most two images were ranked differently and that those images were not ranked as the top or the bottom ones;
- the performance of the algorithm depends to a limited extent from the images, suggesting that it is a robust implementation of the fuzzy computational model it builds upon.

According to those results, the proposed algorithm seems to implement an agent whose behavior resembles that of the human subjects in that:

- its judgment is very similar to those of the subjects as with regard to the most/least similar samples;
- the differences between the rank of the algorithm and those of the subjects are very similar to the differences within the subjects, so as to make the proposed algorithm indistinguishable from any of the subject.

In the future, we will perform further experiments, on larger data sets, including longer words, considering different membership function and different implementations for the similarity measures, in order to ascertain the performance of the proposed algorithm with different handwriting styles, as well as its robustness with respect to the actual values of its parameters.

References

- Blough, D.S. (2001). The Perception of Similarity, in: R.G. Cook (Ed.), *Avian Visual Cognition*, [On-line]. Available: www.pigeon.psy.tufts.edu/avc/dblough/
- Plamondon, R. & Shrihari, S.N. (2000), Online and Off-line Handwriting Recognition: A Comprehensive Survey, *IEEE Trans. on Patt. Anal. Mach. Intell.*, 22(1), pp. 63-84.
- Pekalska, E. & Duin, R.P.W. (2005). The dissimilarity representation for pattern recognition. Foundations and applications. Singapore: World Scientific Press, 2005.
- Tversky, A. (1977). Features of Similarity, *Psychological Review*, 84(4), pp. 327-352.
- Santini, S. & Jain, R. (1999). Similarity Measures. *IEEE Trans. on Patt. Anal. Mach. Intell.*, 21(9), pp. 871-883.
- Powalka, R.K., & al. (1997). Word Shape Analysis for a Hybrid Recognition System, *Pattern Recognition*, 30(3), pp. 421-445.
- Grosicki, E. & al. (2008). RIMES evaluation campaign for handwritten mail processing. *Proc. of the Int. Conf. on Frontiers in Handwriting Recognition*, Montreal, Canada, pp. 1- 6.
- de Borda, J.C. (1781). Mémoire sur les élections au scrutin. Histoire de l'Académie Royale des Sciences, Paris.

Recognize multi-touch gestures by graph modeling and matching

Zhaoxin CHEN ^{a,b}, Eric Anquetil ^a, Harold Mouchère ^b and Christian Viard-Gaudin ^b

^a *INSA de Rennes, Avenue des Buttes de Coësmes, F-35043 Rennes, France*

UMR IRISA, Campus de Beaulieu, F-35042 Rennes, France

^b *LUNAM / UNIVERSITY OF NANTES / IRCCYN, Rue Christian Pauc, 44000, Nantes, France*

{zhaoxin.chen, eric.anquetil}@irisa.fr, {harold.mouchere, christian.viard-gaudin}@univ-nantes.fr

Abstract. Extract the features for a multi-touch gesture is difficult due to the complex temporal and motion relations between multiple trajectories. In this paper we present a new generic graph model to quantify the shape, temporal and motion information from multi-touch gesture. To make a comparison between graph, we also propose a specific graph matching method based on graph edit distance. Results prove that our graph model can be fruitfully used for multi-touch gesture pattern recognition purpose with the classifier of graph embedding and SVM.

1. Introduction

Due to the recent prevalence of multi-touch devices, multi-touch gesture recognition has gained a large interest in the last decade. It is possible to consider two different application frameworks for multi-touch gestures: gestures as direct manipulation or indirect command. The former study is usually based on low-level touch events (e.g., touch-down, touch-move, touch-up) and has been extensively applied in image or map view application (e.g., pinch or spread two fingers to scale an image). The latter is much similar to the character recognition as the recognition procedure is conducted after the entire gesture being performed and triggers a corresponding operation (e.g., copy, paste, etc.). To the best of our knowledge, most research in the latter are based on mono-touch gesture. Our work focuses on the difficulties on multi-touch gesture recognition and tries to make it possible for indirect command.

Unlike mono-touch gesture recognition which tracks the movement of a single point of input, multi-touch gesture often tracks many points of contact in parallel as they appear, move and disappear. The recognition for multi-touch gestures is challenging because of the complex chronological relation between the fingers' trajectories. Consider a two-stroke gesture under a multi-touch input context. Although the shape of the strokes is fixed, the writing order could vary from in-sequence to full-synchronizing as explained in Figure 1. In the work (Hao Lu & Yang Li, 2012), the authors present a GestureCode system recognizing multi-touch gestures with state machines. They achieved around 75% accuracy on a 15-gesture database. In (Kenrick Kin et al., 2012), the Proton++ describes the multi-touch gestures as regular expressions of touch event symbols. GeForMt (Kammer et al., 2010) uses context-free grammars to model multi-touch gestures.

In our prior work (Zhaoxin et al., 2014), we use graph to characterizes the stroke shape information on nodes and stroke spatial and temporal information on edges. In most of the cases, this approach could well recognize the multi-touch gestures which are alike in shape but different in stroke order. However, it only uses some discrete attributes as many previous works (Kenrick Kin et al., 2012) to indicate the state or shape of the strokes. In this paper, we propose an improvement of our prior work that quantifies these relations with numeric features to characterize the stroke shapes, spatial relationships, motion relationships and temporal relationships in the gesture.

2. Represent a multi-touch gesture by graph

Extracting global features has been proven to be efficient for handwriting character, symbol, icon or gesture recognition where the discrimination is mainly made according to the shape of the sample (Don Willems et al., 2009). For the multi-touch gesture case, since each stroke of gesture is no longer only written in sequence, the temporal relation as well as the relative motion relation of strokes should also be characterized. Therefore, in our graph model, we propose to use the node to describe the shape of each stroke and edge to indicate their temporal and motion relation. In the following paragraphs, the graph will be denoted by $g = (V, E)$, where V denotes a finite set of nodes, E denotes a set of edges.

2.1 Preprocessing and sub-stroke representation

In general, an on-line handwriting data is a set of consecutive points which records the coordinate (x, y) , time (t) for each input event. It is unwise to use raw coordinate point as node because the complexity of graph matching in the following procedure is exponential in the number of nodes. We consider to segment each raw strokes S_i into a sequence of straight line sub-strokes (s_1, \dots, s_n) using polygonal approximation. The Ramer-Douglas-Peucker algorithm (Urs Ramer, 1972) is used to find a polygonal chain with few segments that serves as an accurate approximation of the stroke. Each sub-stroke s_i is then represented by a node u_i in the graph with an attribute of 4 components, $u_i = (p_i, a_i, l_i, t_i)$, where p_i is the position (unit square bounding box coordinates) of the center of the sub-stroke, a_i is its angle relative to the horizontal, l_i length of the sub-stroke, t_i contains start

and end times. Each feature is normalized to $[0,1]$. Thus, assume a multi-touch gesture with n strokes, the node set V is represented as

$$V = \{U_1, \dots, U_n\} = \{(u_1^1, \dots, u_{m_1}^1), \dots, (u_1^n, \dots, u_{m_n}^n)\}, \quad [1]$$

where U_i is the subset which contains the nodes belonging to the same stroke S_i . u_i^j is the node which represents the i th sub-stroke of the j th stroke. Once the node set V is obtained, a link edge e^l is built from u_i^j to u_{i+1}^j which indicates the written sequence of a stroke. Since the direction attribute has been contained in node (as angle), the edge only indicates the concatenating relation between nodes.

2.2 Representation for temporal and motion relation between strokes

Differ from the mono-touch handwritten gesture, the multiple strokes in a multi-touch gesture are not performed stroke after stroke. The relative temporal relation between each two strokes could be in-sequence, semi-synchronizing or full-synchronizing. To quantify these relations, we define a fuzzy relative temporal relation function $f_t(s_1, s_2)$ as expressed by equation [2] and illustrated in figure 1,

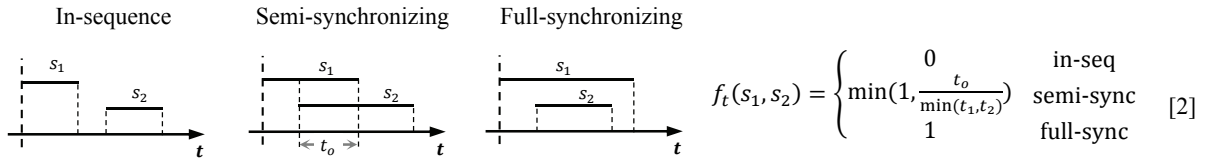


Figure 1. Relative temporal relation between two strokes

where t_o is the time of overlap detected in the semi-synchronizing case, t_1 and t_2 are the time duration for the two strokes. In our graph, this relation function is implemented on each pair of nodes (sub-strokes) which do not belong to same stroke. When value of the relation function is larger than a threshold as $f_t(s_1, s_2) > \lambda$, a synchronization edge e^s is built between the corresponding two nodes.

We now proceed to the modeling of motion information. The synchronization relation obtained above indicates the existence of a relative movement between sub-strokes. This relative movement is the key feature of a multi-touch gesture against a mono-touch gesture. Plenty of previous works (Kenrick Kin et al., 2012) made effort to extract the motion information from the movement. Inspired from the work by (Chi-Min Oh et al., 2011), we measure three kinds of motion from the movement: translation, rotation and scaling. Figure 2 illustrates the computation of the three types of motion between sub-strokes.

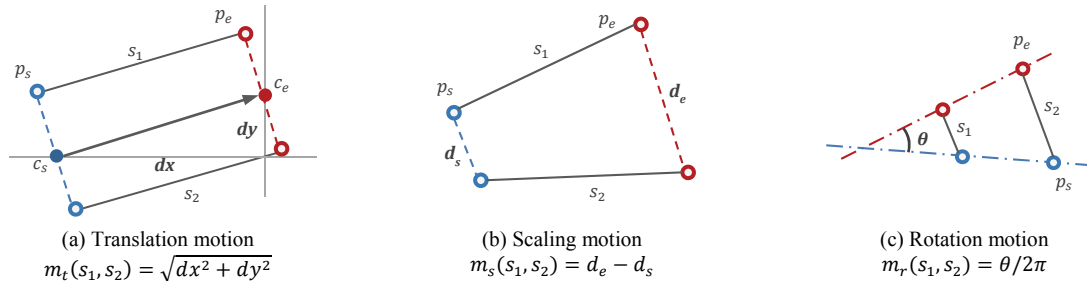


Figure 2. Three types of motion between sub-strokes, p_s and p_e represent the start points pair and end points pair, respectively. Since all the gestures are normalized inside a unit square bounding box, these three values have the same range in $[0,1]$.

Note that it is unnecessary to compute these motion features between all two sub-strokes. The relative movement is meaningful only if two sub-strokes are written synchronously. In other words, these motion features are computed when a synchronization edge e^s is existed between two nodes. Therefore, we assign these three values as the attributes of synchronization edge, $e^s = (m_t, m_s, m_r)$.

On the other hand, in order to capture the sequential relation between the sequential written strokes, we introduce a sequence edge e^q that directs from the last sub-stroke of prewise stroke to the first sub-stroke of the following stroke in our graph. This edge has an attribute t_d as $e^q = (t_d)$, which indicates the time delay between sequential written strokes.

The example in figure 3 considers a bimanual multi-touch gesture performed by a *holding* with left hand and writing 'z' character with right hand synchronously. The preprocessing step firstly resamples the gesture to 4 sub-strokes (s_1, \dots, s_4). Then, we convert each sub-strokes into node in the graph with its shape and duration information as its attribute, i.e. $u_i = (p_i, a_i, l_i, t_i)$. Finally, two link edges e^l and three synchronization edges e^s (since the two strokes are performed synchronously, no sequence edge is built for this gesture) are built between nodes.

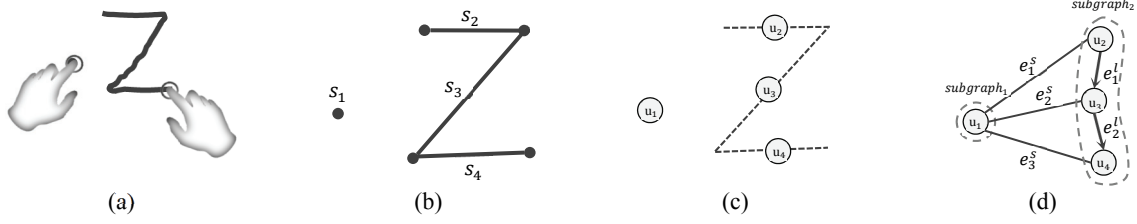


Figure 3. Illustration of the graph representation. (a) Raw input multi-touch gesture. (b) Resampling the raw data to 4 sub-strokes using polygonal approximation. (c) Each sub-stroke s_i is represented by a node u_i with its features (p_i, a_i, l_i, t_i) as attribute. (d) Link edge e^l and synchronization edge e^s are built between nodes.

2.3 Graph matching algorithm

We adopt graph edit distance to compare the dissimilarity between two graphs. Since each graph has multiple sub-graphs, the first step is to find which sub-graph should be compared to which one from one graph to the other. This is a typical assignment problem that can be solved by Munkres' algorithm. The distance of each sub-graph pair is computed by DTW algorithm based on the sequence of nodes $u_i = (p_i, a_i, l_i)$. Optimal matching is then found by Munkres' algorithm that total cost of the sub-graph assignment is minimized. Once we have the nodes' alignment path achieved by DTW, the edit operations on nodes and edges could be inferred from the nodes' DTW path. Consequently, the edit distance of two graphs is defined as:

$$d(G_1, G_2) = \sum_{i=1}^n c(u_i, u_{\varphi(i)}) + \sum_{i=1}^m c(e_i, e_{\varphi(i)})$$

where $c(u_i, u_{\varphi(i)})$ denotes the edit cost for nodes pair, $c(e_i, e_{\varphi(i)})$ is the edit cost for edges pair, φ denotes the assignment function which maps the nodes and edges of the first graph G_1 to the second graph G_2 .

3. Experiments

We describe below a series of experiments to evaluate our graph modeling and graph matching algorithm. The recognition system and database we use will be firstly introduced in this section.

Since we use the graph edit distance to measure the dissimilarity between graphs, a simplest recognition method is the k-Nearest Neighbors (kNN) which classifies an object by a majority vote of its neighbors. Meanwhile, we also implement a graph embedding algorithm introduced in (Kaspar Riesen et al., 2010) to represent the graphs in vector space. The basic idea of this graph embedding algorithm is to represent a graph with a number of dissimilarities to a set of prototypical graphs. Prototypes are iteratively selected from training set under a prototype selection principles named *Targetsphere* (also introduced in (Kaspar Riesen et al., 2010)). A SVM classifier is then trained for the feature vector classification.

We designed a specific gesture database of 4346 samples collected from 21 participants. Based on these gestures, we defined a rotation dependent set (Set45) with 45 different classes and a rotation independent set (Set31) with 31 different classes (Figure 3). Both gesture sets have same content but different labels on some special cases. These gestures are distinguished from shape, temporal and motion information and can be generally separated to two categories. Category A contains bimanual or unimanual multi-touch gestures in which the trajectories are synchronously performed. Gestures in this category vary in shape, numbers of touch finger and motion. To validate the modeling of temporal information, category B contains 4 kinds of multi-stroke gestures which have same shape as some cases in category A but vary in written order.

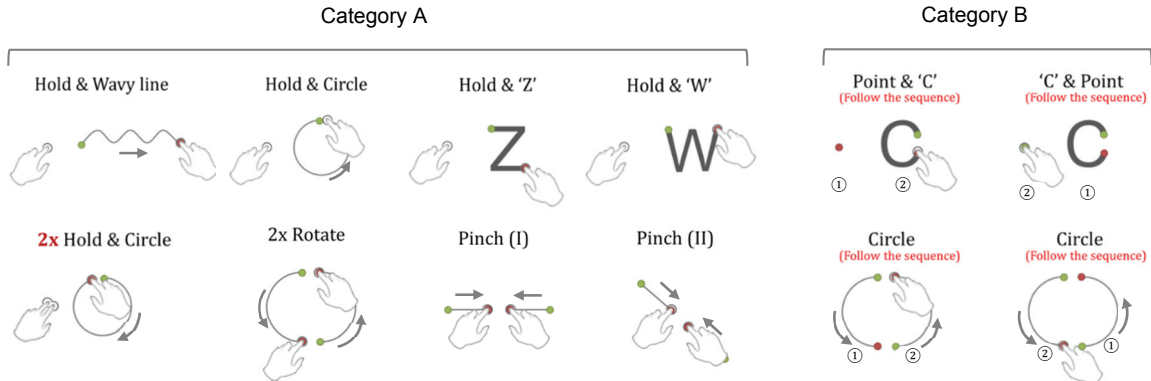


Figure 4. Samples from the gesture database. Category A contains gestures in which the trajectories are synchronously performed. Note that the last two gestures Pinch (I) and Pinch (II) are allocated to different classes in rotation dependent set (Set45) but integrated in the same class in rotation independent set (Set31). Category B consists of two sequential mono-touch gestures which are distinguished from written order.

We conducted our experiments in a 5-fold cross validation and writer independent scheme. In each fold, samples from 6 writers are used for training and 15 writers for test.

4. Results

We compare the recognition accuracy between kNN and graph embedding regarding different numbers of prototypes. Results are given in figure 5.

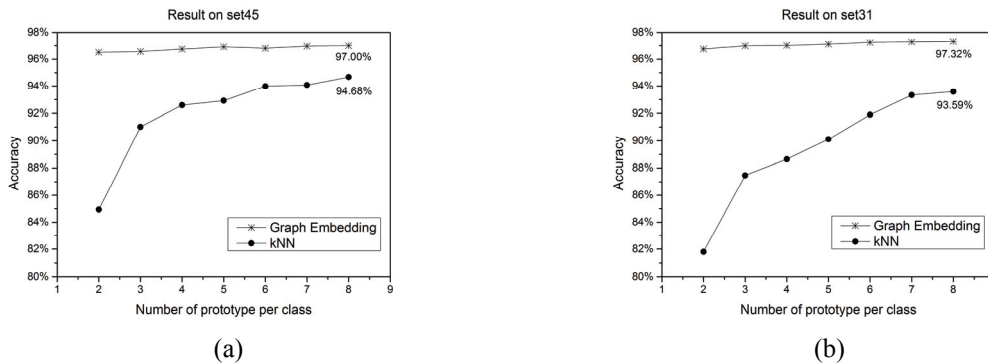


Figure 5. Comparisons of the two recognition systems on both datasets. Accuracies are given as a function of the number of prototypes per class.

The experiments on set45 in Figure 5(a) show that with the increasing of the prototype number, the accuracy of graph embedding system keeps stable around 97% and performs significantly better than kNN system, which increases from 84.93% to 94.68%. Note that even with a limited number of prototypes, the graph embedding with SVM classifier could still obtain a good performance while kNN is not efficient enough. Same trend is also viewed in the result on set31. The graph embedding system performs as good as in set45 while accuracy of kNN system has a slightly decreasing from 94.68% to 93.59%. Results prove that our graph modeling, matching and embedding framework is powerful to extract the discrimination information for multi-touch gesture pattern recognition.

5. Conclusion

In this paper, we propose a new method for modeling the shape, relative temporal and motion information in multi-touch gesture by a model of graph. We extract these information and quantify them as attribute on the nodes and edges in the graph. A way to make a comparison between graphs is also offered that can be used for graph classification. Results show that with the help of graph embedding and SVM classifier, our graph model has the ability to effectively distinguish different multi-touch gestures. Base on this model, in our future work we aim at developing a strategy to detect the pattern of multi-touch gesture at runtime as in (Kenrick Kin, 2012).

References

- Hao Lü, Yang Li (2012). Gesture Coder: A tool for programming multi-touch gestures by demonstration. Proc. of the SIGCHI Conference on Human Factors in Computing Systems (CHI '12). ACM, New York, NY, USA, 2875-2884.
- Kenrick Kin, Björn Hartmann, Tony DeRose, & Maneesh Agrawala. (2012). Proton: multitouch gestures as regular expressions. Proc. of the SIGCHI Conference on Human Factors in Computing Systems (CHI '12). ACM, New York, NY, USA, 2885-2894.
- Kenrick Kin, Björn Hartmann, Tony DeRose, and Maneesh Agrawala. (2012). Proton++: a customizable declarative multitouch framework. Proc. of the 25th annual ACM symposium on User interface software and technology (UIST '12). ACM, New York, NY, USA, 477-486.
- Kammer, D., Wojdziak, J., Keck, M., and Taranko, S. (2010) Towards a formalization of multi-touch gestures. Proc. ITS 2010 (2010), 49–58.
- Zhaoxin Chen, Eric Anquetil, Harold Mouchère, Christian Viard-Gaudin. (2014). A graph modeling strategy for multi-touch gesture recognition. In 14th International Conference on Frontiers in Handwriting Recognition, Pages 259-264, 2014.
- Don Willems, Ralph Niels, Marcel van Gerven, and Louis Vuurpijl. (2009). Iconic and multi-stroke gesture recognition. Pattern Recogn. 42, 12 (December 2009), 3303-3312.
- Chi-Min Oh, Md. Zahidul Islam, and Chil-Woo Lee. (2011). MRF-based Particle Filters for Multi-touch Tracking and Gesture Likelihoods. Proc. of the 2011 IEEE 11th International Conference on Computer and Information Technology (CIT '11). IEEE Computer Society, Washington, DC, USA, 144-149.
- Kaspar Riesen and Horst Bunke. (2010). Graph Classification and Clustering Based on Vector Space Embedding. World Scientific Publishing Co., Inc., River Edge, NJ, USA.
- Kaspar Riesen and Horst Bunke. (2009). Approximate graph edit distance computation by means of bipartite graph matching. Image and Vision computing 27(4), 950-959.
- Urs Ramer. (1972). An iterative procedure for the polygonal approximation of plane curves. Computer Graphics and Image Processing, 1(3), 244–256

The generation of synthetic handwritten data for improving on-line learning

Marta REŽNÁKOVÁ^a, Lukas TENCER^b, Réjean PLAMONDON^c and Mohamed CHERIET^d

^{a,b,d} *École de technologie supérieure (ÉTS), Synchronmedia Lab
Montréal, Québec, Canada (514) 396-8800*

^c *École Polytechnique de Montréal, Laboratoire Scribens
Montréal, Québec, Canada (514) 340-4711*

marta.reznakova@gmail.com, lukas.tencer@gmail.com, rejean.plamondon@plymtl.ca,
mohamed.cheriet@etsmtl.ca

Abstract. In this paper, we introduce a framework for on-line learning of handwritten symbols from scratch. As such, learning suffers from missing data at the beginning of the learning process, in this paper we propose the use of Sigma-lognormal model to generate synthetic data. Our framework deals with a real-time use of the system, where the recognition of a single symbol cannot be postponed by the generation of synthetic data. We evaluate the use of our framework and Sigma-lognormal model by comparison of the recognition rate to a block-learning and learning without any synthetic data. Experimental results show that both of these contributions represent an enhancement to the on-line handwriting recognition, especially when starting from scratch.

1. Introduction

In the recent years, we have seen a growth in the use of smart devices which are often handled with handwritten symbols. In many systems, the use of such symbols requires some pre-definition, which disallows the user to use symbols he finds the best suited for each task. Thus, our work focuses on the on-line learning from scratch, where no pre-definition takes place and it is up to the user to define his own symbols.

However, such a freedom brings challenges from which a low number of samples stands out. Moreover, in this setup, new classes of symbols can be defined one after another and at any time of the use. This leaves a small or even no time for the system's improvement, making it to over-fit, as there is often only one sample per class, and keeps the initial recognition rate low. For this purpose, it is only natural to search for options to obtain more data, so that the system can become more robust sooner and avoid the over-fitting.

There have been several attempts to address the generation of synthetic handwritten data based on a number of models. From these, we list some more recent works, i.e. methods proposing to generate synthetic data based on behavioural models (Schmidt and Lee, 1999), kinematic models (Plamondon and Djoua, 2006), minimization principles (Neilson and Neilson, 2005; Tanaka, 2006) or neural networks (Gangadhar, 2007). Work in this paper is relies on Kinematic Theory describing rapid human movements by Sigma-lognormal (Plamondon et al, 2014; Djoua and Plamondon, 2009; Plamondon et al, 2003).

We apply this method on evolving models capable of on-line learning from scratch. There are some attempts to tackle on-line learning problem (Ditzler, 2010; Yao et.al, 2010; Leistner, 2009; Grabner and Bischof, 2006; Luughofer, 2008). However, very few methods handle also the learning from scratch. Nevertheless there are works also capable of learning from scratch, such as (Angelov, 2010; Almaksour, 2010; Reznakova, 2012; Angelov, 2004). In this work we use ARTIS (Reznakova, 2013), an evolving fuzzy model combined with ART network (Carpenter, 1991).

This paper is organized as follows. In section 2 the proposed framework for on-line learning using synthetic data is described. The Sigma-lognormal model is described in section 3 and the ARTIST model in section 4. Evaluation results are provided in section 5, concluded along with future works in section 6.

2. Framework for online real-time learning using synthetic data

Since in our work we focus on real-time and real-use on-line learning system for handwritten symbols recognition, we need to adjust the use of synthetic data to this problem. To use these data for the learning, a system needs to generate on the fly, just after a new sample is introduced. In the case of block learning, where each new sample waits for all synthetic samples generated from the previous real sample to be learned, the recognition of such new sample is naturally postponed. This happens in case of fast addition of new real samples to the system. To prevent this from happening and to support the real-time on-line learning, we propose a framework described in following.

Figure 1 displays the complete framework we propose in this section. It is divided into two major processes denoted with solid and dashed lines. At the beginning, one sample X is fed to both of these processes, original recognition and learning, and generation of synthetic data. Once a sample is processed by the synthetic data generator, new synthetic data are added to a buffer, waiting for their use. When no real sample is being fed to the system, samples from the buffer can start to be processed. This means that real data have a priority over

synthetic data in the means of feeding them to the model. Once and until no real sample is needed to be processes, buffer incrementally supplies the model with synthetic data that are being picked randomly, i.e. the buffer is being shuffled.

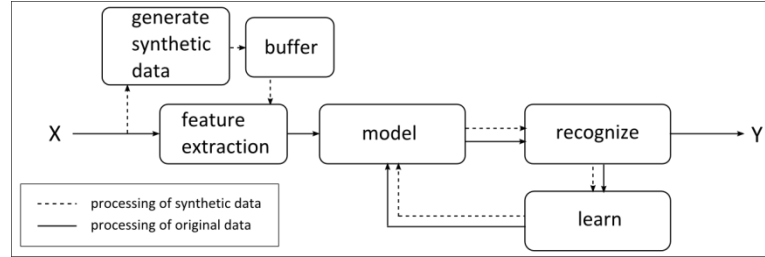


Figure 1. Framework for on-line learning from scratch using synthetic data. X refers to an input sample that is fed to the model and recognized. The information from the recognition process is then used for the learning and new data are added to the model (the model is evolving). The solid line refers to the processing of real samples, where based on recognition the system gives an output Y of a predicted label. The dashed line refers to the additional processes related to the generation of synthetic data.

Ideally, each time a new class is introduced, a number of samples are provided to the system to allow it to learn these classes faster. This framework is thus coping with this problem, avoiding the single-class block learning where it is not appropriate by shuffling its buffer. In the results section, we will note that even though we do not learn classes in blocks right after their occurrence, this framework is able to sustain the recognition rate at the beginning of the learning at the same level as the ideal case.

3. Log-normal model for artificial handwritten data

The Sigma-lognormal model is based on the Kinematic Theory of rapid human movements describing the impulse responses of a neuromuscular network (Plamondon et al, 2014). It is composed of a number of vectors with 6 parameters $p = [t_0, D, \mu, \sigma, \theta_s, \theta_e]$. Details about the various equations of the model have been presented quite often and we refer the reader to the previous reference for more information.

Each time new sample composed of coordinates is introduced to the system, Sigma-lognormal model is derived based on its trajectory. After this, a noise $n_\mu \in [-0.15\mu, 0.15\mu]$, $n_\sigma \in [-0.15\sigma, 0.15\sigma]$ resulting into vector $[0, 0, n_\mu, n_\sigma, 0, 0]$ (Martin-Albo, 2014) is added to the lognormal model. Then, Sigma-lognormal model is translated back to the coordinates that are used for feature extraction. In this work we use geometrical features based on (Reznakova, 2012; Willems, 2008; Peura, 1997; Rubine, 1991). As we can notice in Figure 1, these samples, now represented by a feature vectors, are then supplied to the buffer awaiting their further use.

4. ARTIST

The ARTIST model is based on Takagi-Sugeno fuzzy model (Takagi and Sugeno, 1985). It contains three main parts, i.e. rule generation, antecedent part and consequent part. TS models are represented by rules, where each rule gives an output for every class. The output of one rule is derived from antecedent and consequent parts (1). The antecedent part states, how much an unlabeled sample is similar to samples that have created this rule (x IS a). Then, the consequent part returns the opinion of this rule about the label of the sample ($THEN \{y^i = \beta x \pi^i\}_{i=1..c}$).

$$IF \ x \ IS \ a \ THEN \ \{y^i = \beta x \pi^i\}_{i=1..c} \quad (1)$$

The generation of the rules is based on ART-2A network (Carpenter, 1991). This allows generating the rules in an incremental manner, where the classes do not need to be pre-defined and can be added on the fly. Moreover, rules are not generated with the influence of information about newly added class, but in a completely automatic way.

5. Results

In this work, we focus on real-time on-line learning from scratch. This means that no pre-processing has taken place before the initiation of recognition and learning process. Moreover, each class is introduced on the fly by random order, mostly creating no time for more than one-sample learning. This occurs especially at the beginning of the learning process, when only few samples are known to the system, and thus the recognition is weak. Thus, by using synthetic data, we try to solve this problem, and as we can see in following results, using the Sigma-lognormal model is helpful.

We perform our evaluation on a handwritten gestures dataset (Synchromedia) containing ~33k samples for 17 classes. In this work however, we use only a few samples to better demonstrate the enhancement that using synthetic data offers.

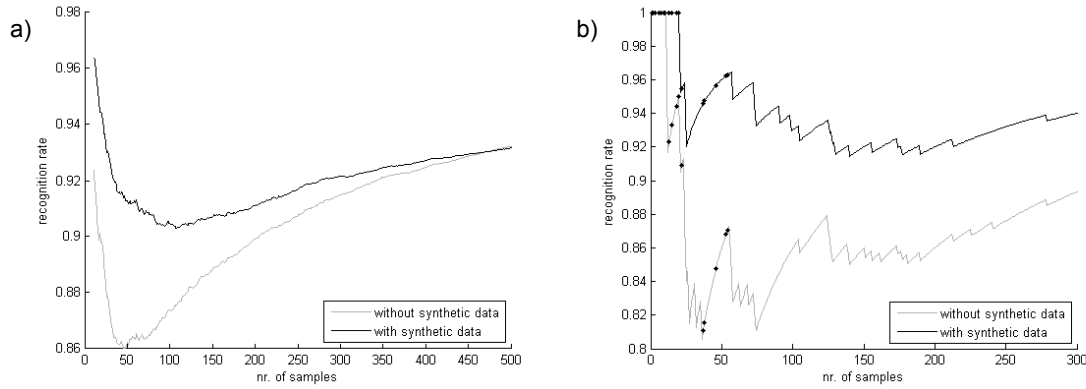


Figure 2. Comparison of recognition rate when using only original data to the use of synthetic data, without (a) and with (b) highlighted times of addition of new class (dots).

In Figure 2a, we compare the initial learning with the use of purely original data to the initial learning using also synthetic data based on our proposed framework. In real-use, there is no fixed time left for the learning of synthetic data, i.e. the time between two consecutive original samples. To mimic this, we let the system select a random number of samples from the buffer within a range $[0, \text{[buffer]}]$, that are allowed to be learned in the time between two consecutive original samples are added. As it can be seen, the use of synthetic data helps the system to learn new classes much faster, which results into higher initial recognition rate, i.e. avoiding drop in the recognition rate after new class is introduced. In Figure 2b, we compare the two methods with highlighted time of when new classes are added to the system. As we can note, at the beginning of the learning process, the recognition rate seems to be very high. This is because when a new class is introduced to the system, no output is expected, and thus no error is recorded. As it is clear from the graph, most of the classes have been introduced at the beginning, which also influences this phenomenon, but here again the use of synthetic data is beneficial.

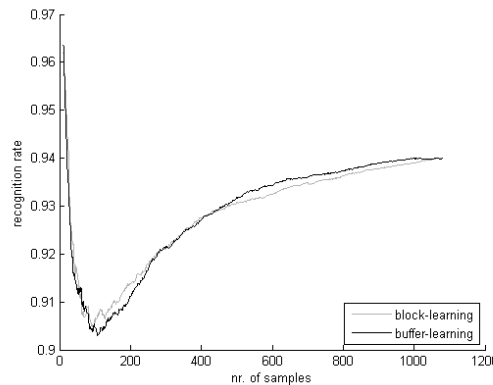


Figure 3. Comparison of recognition rate between block and buffer-based learning.

In Figure 3, we compare the initial recognition rate with block learning, i.e. the system learns all the synthetic data for each newly added sample, to the recognition rate when using buffer, i.e. random number of randomly picked synthetic samples from a buffer are allowed to be learned. As it can be seen, the buffer learning approach is as efficient as the block learning, with the benefit of working real time.

All results except Figure 2b are an average of 50 distinct runs. In all results, we can clearly note that using Sigma-lognormal model for generation of synthetic data improves the recognition rate in the initial learning. Each original sample is used to generate additional 10 samples. This whole process takes on average 12.96 s. The size of the buffer is unlimited, emptying at random occasions, which simulates the real use.

6. Conclusion and discussion

The main goal of this work was to solve the problem of low performance in recognition at the initial phase of the learning. The main causes of this problem are related to learning from scratch and on the fly. However, both of these features are necessary for user-friendly applications, where the user is let to keep his freedom of choice in what symbols he will use on his device.

In this work, we proposed to use synthetic data based on Sigma-lognormal model. Also, we proposed a new framework using shuffled buffer in order to follow the real-time use of the recognition system, when there is

no room to postpone its responses. For evaluation, we have used a random subset of the samples from handwritten symbols database in order to show the performance of our propositions for the initial phase of the learning process.

We have shown that the use of synthetic data indeed helps to increase the performance which is so needed for on-line learning and recognition. We have also shown that the use of buffer helps to retain similar level of recognition rate as compared to the block learning.

In our future work, we will focus on the adjustment of noise added to the Sigma-lognormal model, to be more suited for the purpose of synthesis of handwritten symbols. Also we will work on adjusting the number of generated synthetic data, in order to enhance the system and at the same time to prevent big amounts of data. Another study of interest will be to explore the behaviour of the system when noisy data are being synthesized.

Acknowledgement

This work was supported by the Social Sciences and Humanities Research Council of Canada (SSHRC) as well as the Natural Sciences and Engineering Research Council of Canada (NSERC).

References

- Abdulah Almaksour, E. A. (2010). Evolving Fuzzy Classifiers: Application to Incremental Learning of Handwritten Gesture Recognition Systems. Istanbul: International Conference on Pattern Recognition (ICPR).
- Angelov, P., Filev, D. P., & Kasabov, N. (2010). Evolving Intelligent Systems: Methodology and Applications. In J. W. Sons. New York.
- Carpenter, G., Grossberg, S., & Rosen, D. B. (1991). ART 2-A: An adaptive resonance algorithm for rapid category learning and recognition. *Neural Networks*.
- Ditzler, G., Muhlbaier, M. D., & Polikar, R. (2010). Incremental Learning of New Classes in Unbalanced Datasets: Learn + + .UDNC. *Multiple Classifier Systems*, 33-42.
- Djioua, M., & Plamondon, R. (2009). Studying the variability of handwriting patterns using the Kinematic Theory. *Human Movement Science*, 588-601.
- Don J.M. Willems, a. R. (August 19, 2008). *Definition for Features used in Online Pen Gesture Recognition*.
- Gangadhar, G., Joseph, D., & Chakravarthy, V. (2007). An oscillatory neuromotor model of handwriting generation. *Int. J. Doc. Anal. Recognit.*, 69–84.
- Grabner, H., & Bischof, H. (2006). On-line Boosting and Vision. *Computer Vision and Pattern Recognition, 2006 IEEE Computer Society Conference on*, (pp. 260-267).
- Leistner, C., & Bischof, H. (2009). On-line Random Forests. *IEEE 12th International Conference on*, (pp. 1393-1400).
- Luughofer, E. D. (2008). FLEXFIS: A Robust Incremental Learning Approach for Evolving Takagi-Sugeno Fuzzy Models. *IEEE Transactions on fuzzy systems*, vol. 16, no. 6, 1393-1410.
- M. Peura, J. I. (1997). Efficiency of Simple Shape Descriptors. *Advances in Visual Form Analysis*, 443-451.
- Martin-Albo, D., Plamondon, R., & Vidal, E. (2014). Training of On-line Handwriting Text Recognizers with Synthetic Text Generated Using the Kinematic Theory of Rapid Human Movements. *14th International Conference on Frontiers in Handwriting Recognition*, (pp. 543-548).
- Neilson, P., & Neilson, M. (2005). An overview of adaptive model theory: solving the problems of redundancy, resources and nonlinear interactions in human movement control. *J. Neural Eng.*, 279–312.
- Plamen P. Angelov, D. P. (February 2004). An Approach to Online Identification of Takagi-Sugeno Fuzzy Models. *IEEE Transactions on system, man, and cybernetics*, vol. 34, 484-498.
- Plamondon, R., & Djioua, M. (2006). A multi-level representation paradigm for handwriting stroke generation. *Hum. Mov. Sci.* 25, 586–607.
- Plamondon, R., Feng, C., & Woch, A. (2003). A kinematic theory of rapid human movement. Part IV: a formal mathematical proof and new insights. *Biol. Cybern.* 89, 1266-138.
- Plamondon, R., O'Reilly, C., Galbally, J., Almaksour, A., & Anquetil, E. (2014). Recent developments in the study of rapid human movements with the kinematic theory: Applications to handwriting and signature synthesis. *Pattern Recognition Letters*, 225-235.
- Režnáková, M., Tencer, L., & Cheriet, M. (2012). Online handwritten gesture recognition based on Takagi-Sugeno fuzzy models. *11th International Conference on Information Science, Signal Processing and their Applications (ISSPA)*.
- Režnáková, M., Tencer, L., & Cheriet, M. (2013). ARTIST: ART-2A driven Generation of Fuzzy Rules for Online Handwritten Gesture Recognition. *12th International Conference on Document Analysis and Recognition, ICDAR '13*.
- Rubine, D. (1991, July). Specifying gestures by example. *SIGGRAPH Comput. Graph.*, 25(4), 329--337.
- Schmidt, R., & Lee, T. (1999). Motor Control and Learning: A behavioral Emphasis. *3rd Ed. Human Kinetics*, (p. 493p.). Champaign Illinois.
- Synchromedia. (n.d.). <http://www.synchromedia.ca/web/ets/gesturedataset>.
- Takagi, T., & Sugeno, M. (1985). Fuzzy Identification of Systems and Its Applications to Modeling and Control. *IEEE Transactions on systems, man, and cybernetics*, vol. SMC-15, no. 1, 116-132.
- Tanaka, H., Krakauer, J., & Qian, N. (2006). An optimization principle for determining movement duration. *J. Neurophysiol.*, 3875–3886.
- Yao, M., Qu, X., Gu, Q., Ruan, T., & Lou, Z. (2010, June). Online PCA with adaptive subspace method for real-time hand gesture learning and recognition. *W. Trans. on Comp.*, 9(6), 583--592.

Omega-Lognormal Analysis of Oscillatory Movements as a Function of Brain Stroke Risk Factors

Albert Bou Hernandez¹, Andreas Fischer^{1,2,3}, and Réjean Plamondon¹

¹Laboratoire Scribens, École Polytechnique de Montréal, Canada
{albert.bou hernandez, andreas.fischer, rejean.plamondon}@polymtl.ca

²DIUF Department, University of Fribourg, Switzerland, andreas.fischer@unifr.ch

³iCoSys Institute, University of Applied Sciences and Arts Western Switzerland, andreas.fischer@hefr.ch

Abstract.

The development of predictive tools has been commonly utilized as the most effective manner to prevent illnesses that strike suddenly. Within this context, investigations linking fine human motor control with brain stroke risk factors are considered to have a high potential but they are still in an early stage of research. The present paper analyses neuromuscular features of oscillatory movements based on the Omega-Lognormal model of the Kinematic Theory. On a database of oscillatory movements from 120 subjects, we demonstrate that the proposed features differ significantly between subjects with and without brain stroke risk factors. This promising result motivates the development of predictive tools based on the Omega-Lognormal model.

1. Introduction

A brain stroke, or cerebrovascular accident, is characterized by the sudden manifestation of combined cerebral circulatory disorders that negatively affect the vasculature of the brain. A brain stroke episode results in necrosis of certain brain cell types, which causes irreversible damage to an array of neurological functions in 22% to 25% of the patients and death within one year for 25% of the patients [1]. Approximately 795.000 people experience a new or recurrent stroke annually. Therefore, on average, someone dies of a stroke every 4 minutes [2].

Furthermore, brain strokes are sudden events and most of the time they occur unexpectedly. An effective method of addressing this medical issue is therefore prevention through the development of predictive tools. Handwriting recognition tools have emerged as one such possible solution [3, 4]. It is not the first time that pattern analysis of fine motor control is employed in disease prevention. Noticeable results have been achieved previously in the prevention of other diseases, such as Parkinson disease [5] or Schizophrenia [6].

It has been reported recently that some brain stroke risk factors can be associated with the deterioration of several cognitive psychomotor characteristics [7], which are obtained from the lognormal handwriting model of the Kinematic Theory [8, 9, 10]. In this paper, we focus on one of the movement modalities suggested in [7], namely oscillatory movements at maximum frequency, and investigate the feasibility of developing predictive tools in more detail. The study and analysis of oscillatory movements has a strong history in human motor control, from a theoretical and model perspective [11, 12, 13] to applications in various field [13, 14].

To achieve our goal, a database containing the handwriting movements of 120 subjects with and without brain stroke risk factors is analysed using the Omega-Lognormal model [7]. We propose a set of seven neuromuscular features based on the model and demonstrate with ANOVA tests that four of these differ significantly between subjects with and without risk factors. The results obtained can be

considered as an initial step towards the development of a tool to determine if the performer of oscillatory movements has brain stroke risk factors or not.

The remainder of this paper is organized as follows. First, the experimental protocol for the acquisition of oscillatory movements is detailed in Section 2. Then, the data analysis based on the Omega-Lognormal model and the proposed neuromuscular features are presented in Section 3. Finally, experimental results are provided in Section 4 and conclusions are drawn in Section 5.

2. Experimental Protocol

For the assessment of the proposed method, a database containing digitized information of oscillatory movements from 120 subjects was used. Within the database, 57 subjects considered as healthy are mixed with 63 exhibiting some of the following brain stroke risk factors (abbreviation, number of subjects affected): diabetes mellitus (DM; 15), obesity (OB; 10), hyper-tension (HT; 40), hypercholesterolemia (HC; 28), cardiac disease (CD; 24), and cigarette smoking (CS; 13). From these 63 participants, 25 had only one risk factor, 18 had two, 12 had three, 7 had four, and 1 had five. In order to evaluate a

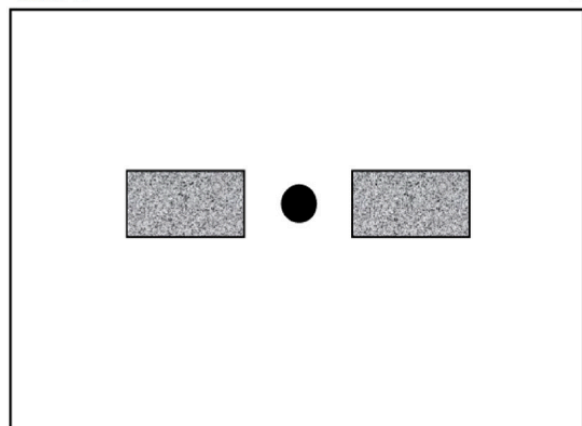


Figure 1 | Guiding sheet for the oscillatory movements test. The black circle and the gray areas indicate respectively the starting and the target zones

wide age range, 27 of the participants are between 25 and 39 years old, 31 are between 40 and 54, 33 are between 55 and 69 and 29 are between 70 to 85 years old. Moreover the distribution among genders is almost balanced as the sample contains 68 women and 52 men.

During the performance of the trial, a Wacom Intuos2 tablet was used to digitize the 2D Cartesian coordinates of the pen tip at a sampling frequency of 200 Hz.

To accomplish the trial, the subjects were asked to perform oscillatory movements with the pen tip as fast as possible between two targets during ten seconds, after a start signaled by an auditory cue. Additionally, guiding sheets were used to indicate to the participants the starting position and the targets to hit as illustrated in Figure 1. The movements were performed with the dominant hand. 112 participants reported themselves as right-handed.

It is also important to mention that no practice or learning period was allowed before the exercise and only one acquisition of data was permitted. After removing outliers, 115 subjects were kept in the database. More information about the database can be found in [7].

3 Data Analysis

3.1 Omega-Lognormal Model

The Kinematic Theory of rapid human movements is a set of models that describe human handwriting movements using a unique framework based on the delta-lognormal law. A basic unit representing a pen stroke is built up from lognormals. These models grant a fitting reconstruction of handwriting velocity profile [15]. Amid this set, the Omega-Lognormal model, which analyses the motion of alternating sequences of lognormals, is the most appropriate model to analyse oscillating movements in one dimension. It has already been employed in previous studies [7] and is defined by:

$$\Omega\Lambda = \sum_{i=1}^N D_{1i}\Lambda(t - t_{01i}; \mu_{1i}, \sigma_{1i}) - \sum_{j=1}^M D_{2j}\Lambda(t - t_{02j}; \mu_{2j}, \sigma_{2j})$$

with $|N - M| \in \{0,1\}$ and $\Lambda(t - t_{0i}; \mu_i, \sigma_i)$ defined as:

$$\Lambda = \frac{1}{\sigma\sqrt{2\pi}(t-t_0)} \exp\left(\frac{(\ln(t-t_0)-\mu_i)^2}{-2\sigma_i^2}\right)$$

The individual pen strokes are initialized at time t_0 and the distance covered is D . The parameters μ and σ are related to the neuromuscular execution of the pen stroke. Oscillatory movements are modelled as a sequence of

alternating pen strokes in opposite direction.

For parameter extraction from the original pen trajectory, a modified version of the Robust Xzero extractor was used [16, 17]. In order to evaluate the quality of the model, the signal-to-noise ratio is computed as a measure of similarity between the original velocity v_{org} and the reconstructed velocity v_{rec} [8]:

$$SNR = 10 \log \left(\frac{\int v_{org}^2 dt}{\int (v_{org} - v_{rec})^2 dt} \right)$$

Figure 2 shows an example of a well-fitted velocity reconstruction using the Omega-Lognormal model. In order to reach a more precise SNR, the original digitized data was first interpolated and low-pass filtered to remove high frequency components introduced during the digitization.

3.2 Outlier Removal

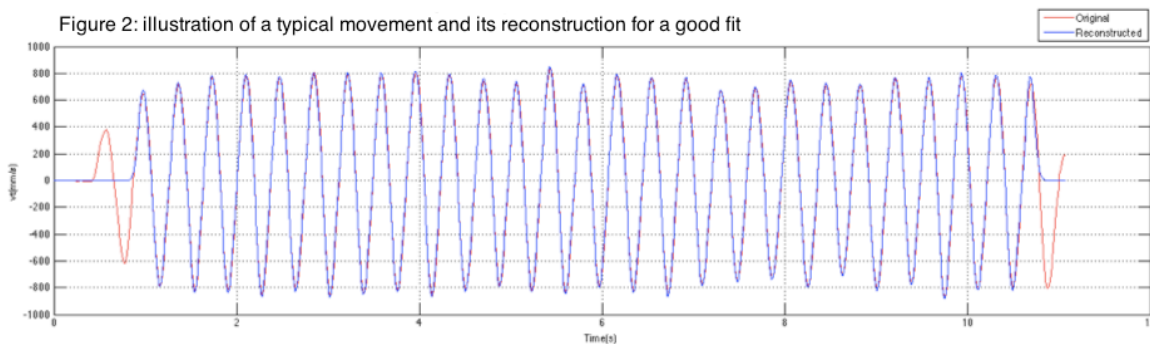
Since the parameter extraction software finds local minimal solutions, possible outliers or unusual values generated during the digitizing stage or the parameter extraction process have been removed.

A certain transient period at the beginning of the signal could be considered as less stable since the trials were performed without previous training. Also, the last movements of the writers could be affected and consequently altered by muscular fatigue due to the process itself. Hence, the three first and the three last lognormals were removed to minimize these fluctuations.

An approximate distance of 180 mm separated the outer limits of the two target zones. Since some writers could execute the pen strokes in a somewhat diagonal or even bending fashion, the effective distance covered by the pen could be somewhat larger than 180mm. Additionally, taking into account that the model parameter D reflects the pen stroke distance without the influence of the next pen stroke in opposite direction, a final value of 200 mm was considered as an upper bound for this parameter. Similarly, a lower bound of 45mm has been fixed, which is a bit less than the distance between the inner limits of the target zones.

Finally, a minimum SNR was required for each lognormal to be taken into account. Several reports have pointed out that a quality over 15 dB is sufficient for human movement analysis [10].

After this process 8326 lognormals remained from the original database containing 9412 (11,53% of the lognormals have been removed). From this percentage,



7,33% of the lognormals were removed from the extremes directly and 4,2% were removed because they did not fit within the limits mentioned above.

At the end of the cleaning process several lognormals still remain for all writers. However, if the remaining number of lognormals is low, a statistical analysis may not be reliable. This could be either due to a large number of removed outliers or due to an unusual number of pen strokes during the experiment. All writers with less than 15 lognormals (4 writers) have been excluded from the database.

3.3 Proposed Features

In order to potentially discriminate between subjects with and without brain stroke risk factors, we propose a set of seven neuromuscular features based on the Omega-Lognormal model:

- D, μ, σ : The first three features correspond directly with model parameters, that is the neuromuscular input command D , which correspond to the pen stroke distance (when executed in isolation without influence of the next pen stroke in opposite direction) and the two parameters μ and σ related to the logtime delay and the logresponse time of the neuromuscular system responding to the command.

- $\Delta t_0, f_0$: The two next features describe the frequency of the pen strokes. Δt_0 is the time difference between the t_0 parameters of two consecutive lognormals and f_0 is the dominant frequency extracted by means of fast Fourier transform (FFT). The FFT has been computed with Matlab over the reconstructed signal using 1024 points. Most of the subjects present various components in the frequency domain; f_0 corresponds to the frequency of the component with the maximum power.

- $SNR, SNR/nblog$: The final two features are concerned with the model quality. SNR is the signal-to-noise-ratio (see Section 3.1) and $SNR/nblog$ is normalized with the number of lognormals.

For the features D, μ, σ , and Δt_0 the mean value of the lognormals is considered for each oscillatory movement.

4 Experimental Evaluation

4.1 Statistical Analysis

In an experimental evaluation, we aim to demonstrate that the proposed neuromuscular features differ between the groups of subjects with and without brain stroke risk factors. To that end, we perform a one-way ANOVA test for each feature. The null hypothesis that the population means are the same is rejected if, for at least one of the features, the p-value is

$$p < \frac{0.05}{7} = 0.0071$$

taking into account the commonly used significance level $\alpha = 0.05$ and considering the Bonferroni correction, that is an adjustment for multiple parameter testing (7 tests in our case, one for each feature) which compensates for the fact that a significant result could be observed by chance.

4.2 Results

Table 1 displays the results obtained from the one-way ANOVA tests. Distributed horizontally in columns, the table shows all the features considered in this paper. Beneath each feature, the corresponding p-value is displayed. Likewise, the mean of the considered features is presented for subjects with and without risk factors (RF) in the table.

Significant results taking into account the Bonferroni correction are marked in bold. In four out of seven cases, the tests are significant, demonstrating that the proposed neuromuscular features, indeed, differ between subjects with brain stroke risk factors and subjects without risk factors.

The results obtained for the individual tests reveal which features are most discriminative to classify writers with respect to their brain stroke risk factors condition and which are less discriminative. Each of the three groups of features (see Section 3.3) contains at least one significant test result. The lowest p-values are reported for the second group of features related to the frequency of lognormals. The mean frequency is significantly lower for subjects with risk factors, that is they could not execute the oscillatory movements as fast as the subjects without risk factors. In the first group of features, the σ parameter of the Omega-Lognormal model has proven to be most discriminative and in the third group, the normalization of the SNR with the number of lognormals was necessary to achieve a significant result in accordance with previous studies [8, 19, 20].

In order to develop predictive tools based on the Omega-Lognormal model, these features could be pointed out as discriminative with respect to brain stroke risk factors. A combination of these features is expected to provide the best prediction result.

5 Conclusions

In this paper, we have investigated possible links between fine human motor control and brain stroke risk factors with

Table 1: ANOVA test p-values for the proposed features

	D	μ	σ	Δt_0	f_0	SNR	$SNR/nblog$
P-value	0.0285	0.1545	7.21e-05	2.13e-05	2.02e-07	0.326	1.99e-05
Mean without RF	124.6	-0.171	0.041	0.115	5.0	20.4	0.27
Mean with RF	116.2	-0.172	0.059	0.170	3.5	21.1	0.46

a view to prediction tools. We have focused our study on oscillatory movements at maximum frequency and proposed a set of seven neuromuscular features based on the Omega-Lognormal handwriting model that aim to distinguish subjects with risk factors from subjects without risk factors.

A database including 120 subjects, highly balanced in terms of gender, brain stroke risk factors, and age range has been analysed based on the Omega-Lognormal model. One-way ANOVA tests with Bonferroni correction have demonstrated that the features differ, indeed, between subjects with and without risk factors.

The results highlight the possibility of developing predictive tools based on some of the proposed features. The application of pattern recognition and machine learning techniques using the most discriminative features of the model seem to be the next natural step in this process.

Acknowledgements

This work has been supported by the Swiss SNSF grant P300P2-151279 to A. Fischer and the Canadian NSERC grant RGPIN-915 to R. Plamondon.

References

- Insight, M., *U.S. Markets for Peripheral Vascular Stents*. 2011. Report #A254.
- Go, A.S., et al., *Heart Disease and Stroke Statistics—2014 Update*. Circulation, 2014.
- Plamondon, R., O'Reilly, C., Galbally, J., Almaksour, A., Anquetil, E., *Recent developments in the study of rapid human movements with the kinematic theory: Applications to handwriting and signature synthesis*. Pattern Recognition Letters, 2014. 35: p. 225-235.
- Tappert, C.C., C.Y. Suen, and T. Wakahara, *The State of the Art in Online Handwriting Recognition*. IEEE Trans. Pattern Anal. Mach. Intell., 1990. 12(8): p. 787-808.
- Van Gemmert, A.W.A., C.H. Adler, and G.E. Stelmach, *Parkinson's disease patients undershoot target size in handwriting and similar tasks*. Journal of Neurology, Neurosurgery & Psychiatry, 2003. 74(11): p. 1502-1508.
- Caligiuri, M.P., Teulings, H-L., Dean, C.E., Niculescu, A.B., Lohr, J., *Handwriting movement analyses for monitoring drug-induced motor side effects in schizophrenia patients treated with risperidone*. Human Movement Science, 2009. 28(5): p. 633-642.
- O'Reilly, C., Plamondon, R., and Lebrun, L-H. *"Linking brain stroke risk factors to human movement features for the development of preventive tools"*. Frontiers in Aging Neuroscience, 2014. 6.
- Plamondon, R., O'Reilly, C., Rémi, C., Duval, R.C., *"The lognormal handwriter: learning, performing and declining"*, Frontiers in Psychology: Cognitive Science doi: 10.3389/fpsyg.2013.00945, Special Issue in Cognitive Science, Writing words: From brain to hand(s), Topic Editor(s): Sonia Kandel, Marieke Longcamp, pp 1-14, 2013.
- Plamondon, R., O'Reilly, C., Ouellet-Plamondon, C., *"Strokes against Stroke-Strides for Strides"*, Pattern Recognition, 44 (3): 929-944, 2014.
- Djioua, M. and R. Plamondon, *A new algorithm and system for the characterization of handwriting strokes with delta-lognormal parameters*. Pattern Analysis and Machine Intelligence, IEEE Transactions on, 2009. 31(11): p. 2060-2072.
- Kay, B.A., Saltzman, E.L. & Kelso, J.A.S. (1991). *"Steady-state and perturbed rhythmical movements: Dynamical modeling using a variety of analytic tools"*. Journal of Experimental Psychology: Human Perception and Performance, 17, 183-197.
- Grossberg, S., Pribe, C., Cohen, M., *"Neural control of interlimb oscillations"*, Biological Cybernetics 77 (2), 1997, pp 131-140.
- André, G., Kostrubiec, V., Buisson, J.C. Albaret, J.M., Zanone, P-G. *"A parsimonious oscillatory model of handwriting"* Biol Cybern. 2014, DOI 10.1007/s00422-014-0600-z
- S. Athenes, I. Sallagoity, P-G. Zanone, J-M. Albaret, *Evaluating the coordination dynamics of handwriting*, Human Movement Science 23 (5) 2004, pp. 621-641
- Plamondon, R., *A kinematic theory of rapid human movements: Part III. Kinetic outcomes*. Biological Cybernetics, 1998. 78(2): p. 133-145.
- O'Reilly, C. and R. Plamondon. *Design of a neuromuscular disorders diagnostic system using human movement analysis*. in *Information Science, Signal Processing and their Applications (ISSPA), 2012 11th International Conference on*. 2012.
- O'Reilly, C. and R. Plamondon. *Looking for the brain stroke signature*. in *Pattern Recognition (ICPR), 2012 21st International Conference on*. 2012.
- Woch, A. and R. Plamondon, *Characterization of bi-directional movement primitives and their agonist-antagonist synergy with the delta-lognormal model*. Motor control, 2010. 14(1): p. 1-25.
- Duval, T., Rémi, C., Plamondon, R., O'Reilly, C., *"On the Use of the Sigma-Lognormal Model to Study Children Handwriting"* Proc. 16th Biennial Conf. of the International Graphonomics Society, Nara, Japon, juin 2013 (26-29)
- Van Gemmert, A., Plamondon, R., O'Reilly, C., *"Using the Sigma-lognormal model to investigate handwriting of individuals with Parkinson's disease"*, Proc. 16th Biennial Conf. on the International Graphonomics Society, Nara Japon, juin 2013, (119-122).

Monitoring Neuromotricity On-line: a Cloud Computing Approach

Olivier LEFEBVRE ^a, Pau RIBA ^b, Jules GAGNON-MARCHAND ^a, Charles FOURNIER ^a, Alicia FORNES ^b,
Josep LLADOS ^b and Réjean PLAMONDON ^a

^a *Scribens Laboratory. Polytechnique Montréal*
2500, Chemin de Polytechnique
H3T 1J4, Montréal, CANADA

^b *Computer Vision Center and Department of Computer Science. Universitat Autònoma de Barcelona*
Ed.O, Campus UAB
08193, Bellaterra, SPAIN

olivier.lefebvre@polymtl.ca, priba@cvc.uab.es, jules.gagnon-marchand@polymtl.ca,
charles.fournier@polymtl.ca, afornes@cvc.uab.es, josep.llados@uab.cat, rejean.plamondon@polymtl.ca

Abstract. The goal of our experiment is to develop a useful and accessible tool that can be used to evaluate a patient's health by analyzing handwritten strokes. We use a cloud computing approach to analyze stroke data sampled on a commercial tablet working on the Android platform and a distant server to perform complex calculations using the Delta and Sigma lognormal algorithms. A Google Drive account is used to store the data and to ease the development of the project. The communication between the tablet, the cloud and the server is encrypted to ensure biomedical information confidentiality. Highly parameterized biomedical tests are implemented on the tablet as well as a free drawing test to evaluate the validity of the data acquired by the first test compared to the second one. A blurred shape model descriptor pattern recognition algorithm is used to classify the data obtained by the free drawing test. The functions presented in this paper are still currently under development and other improvements are needed before launching the application in the public domain.

1. Introduction

Over the years, at Scribens Laboratory, we have developed algorithms for extracting lognormal parameters that describe handwriting movements. The study of the evolution of these parameters over a longer period of time would allow us to analyze changes in a user's neuro-motor skills. We could monitor the improvements of a child learning to write or detect the loss of neuro-motor skill. These programs were until now restricted to Wacom tablets connected to standard computers and screens. The goal of this work is to transfer the software to a portable Android tablet touch screen to eventually make it more easily accessible to physicians and clinicians.

To accomplish this, Polytechnique Montréal and the Computer Vision Center (Barcelona, CVC) have initiated a collaborative project that aims to create an Android application that is able to:

- Analyze a patient's handwriting strokes to determine relevant biomedical data (Polytechnique Montréal);
- Recognize specific patterns or shapes from a patient's drawing or writing (CVC).

Once completed and fully integrated, this application will be used as a tool for biomedical research. The effects of young children (5-7 years old) learning to write and the effects of aging have already been proven (Plamondon et al. 2013). Another important application for this tool is to characterize a patient's health and follow its progression through time (O'Reilly et al. 2010).

The pattern recognizer developed by the CVC is included in the application to perform word or drawing spotting to assess the potentiality of recovering the same biomedical information about a subject state (learning/aging/health) without the boundaries of a highly parameterized test. If this hypothesis is confirmed, a whole new area of possible applications could be created.

2. Implementation choices and project definition

By using the Android platform, which is very popular for new electronic tablet and smart phone technology, the application will be highly accessible to a very large portion of the targeted population. A Samsung Galaxy Note 10.1 2014 edition was used to test the application.

Because the two algorithms used in the application to analyze biomedical data, namely the Delta-lognormal and Sigma-lognormal algorithms (Plamondon et al. 2009), require a lot of resources (memory, computation power), a distant server is used to take over the analysis and the digitizer (tablet, smart phone, etc.) serves as an acquisition module with a user interface.

This interface first presents itself to the user with two main choices: biomedical tests and free drawing session. The first choice leads to a panel of options representing different predefined highly parameterized and bounded tests that are currently used at the Scribens laboratory (O'Reilly et al. 2014) while the second choice leads to a free drawing area. Here, a shape recognizer algorithm detects shapes, and the associated relevant information about the subject's strokes is retrieved afterwards.

The choice of the shapes for the recognizer to detect is important because we must confirm that a free drawing stroke is similar to a stroke made within a highly parameterized test. The triangle is a good example of shape that can be used (O'Reilly et al. 2011). Therefore, we first focused on the triangle as a shape to be recognized. Other shapes may be defined later on, and the platform's modular design allows for easy integration of new options. The database in the cloud will also have to be organized such that the data corresponding to a specific type of freehand or constrained drawing of a particular shape are easy to recover and analyze.

A Google Drive account was used as a cloud to facilitate the communication between the digitizer and the server. This approach has the advantage of storing all the relevant data in a cloud which allows the application part of the project to be developed independently from the server part. It also procures a facilitated way to transfer and store the data files via Google's application programming interfaces and file manipulation options.

3. Digitizer using the Android platform

This section presents the user interface developed on the Android platform to acquire biomedical data from user handwriting strokes. The tablet used for this project is the Samsung Galaxy Note 10.1 2014. The first thing that we did was replace the SPencanvas data acquisition class with a standard canvas, written in Java, which increased the sampling frequency from 25 to 60 Hz. Then, we focused our efforts on designing three tests: the single stroke test, the triangle test and the free drawing area.

The single stroke test is quite simple: after hearing an audio stimulus, the user must perform a single rapid movement from a black dot at the centre of the screen (start zone) to one of the grey areas situated on either side of the screen (end zones) (Figure 1a).

Figure 1b presents the second biomedical test available on the application, the triangle shape test. The user must draw the triangle shape appearing on the screen using a single sequence of strokes. This shape is defined by three circles that represent the corners of the triangle and by three coloured bands that form the edges of the triangle. The user must start their stroke within the circle identified with tag 1, reach the circle tagged with the number 2 and then the one tagged with a 3 before finishing their stroke back in the first circle. Like the previous test, the stroke must not be drawn until the audio stimulus is launched.

Those two interfaces contain a drawing area (1) where the user must execute the test, a Tutorial button (2) to assist the user by presenting tutorial slides and finally a Settings button (3) to be able to modify the test settings. The Help button (4) appears only when a user needs to be reminded of the test rules. The last button (5), with the user's name, is used to access the user settings and to log out from the application. This last button is always available throughout the application except from the login interface.

Figure 1c presents the free drawing interface, which shows a drawing area, a Settings button to change parameters such as the colour of the pen used, and the user's name button. It also has a Delete button (6) to erase the drawing area and start a new drawing. Functionalities such as saving a drawing or editing a line (without changing the relevant biomedical data) could be added in the future to increase the interface's user-friendliness.

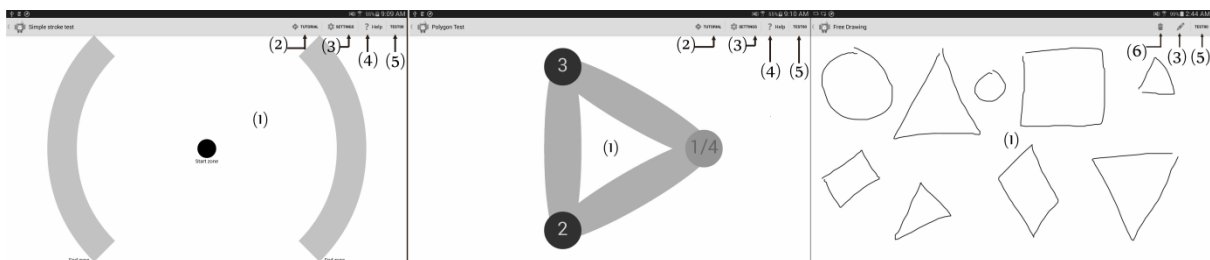


Figure 1: a) the simple stroke test interface, b) the triangle shape test interface and c) the free drawing interface.

The first two interfaces are highly parameterized, and the properties of the geometrical features and of the audio stimulus signal can be modified when accessing the settings menu with the appropriate button (3 on Figures 1a and 1b). Table 1 presents the properties that can be modified for each of the two interfaces and the audio stimulus signal with their associated default values in parentheses. This allows the experimenter to adjust the two tests for each user if necessary. For example, if a particular user suffers from Parkinson's disease, the start zone radius of the interfaces may need to be augmented to accommodate them.

Table 1: The settings of the two interfaces including the properties of the audio stimulus signal. Default values follow the setting in parentheses.

Simple stroke test interface
Velocity threshold (50 mm/s), start zone radius (2.5 mm), end zone inner radius (20 mm), end zone outer radius (50 mm), end zone angle (45°), start zone colour (black), end zone colour (grey)
Triangle test interface

Velocity threshold (50 mm/s), first circle radius (10 mm), second and third circle radius (10 mm), triangle radius (40 mm), edge width (20 mm), triangle orientation (0°), first circle colour (green), second and third circle colour (blue), edge colour (turquoise)
Audio stimulus signal
Frequency (1000 Hz), duration (0.5 s), minimum start time (1 s), maximum start time (10 s), volume (50%)

The velocity threshold parameter is used to limit the movement at the beginning of the stroke before the movement is initialized. The end zone angle parameter in the simple stroke test interface represents the angle of the end zone's arc divided by two. For the triangle test interface, the triangle orientation parameter is the angle between the horizontal line that splits the screen in half on its height and the centre of the first circle. The minimum and maximum start time associated with the audio stimulus signal represent the limits of the uniform distribution of the delay before the audio stimulus is launched. The delay value is picked randomly in this distribution. Every kind of error is distinguished and the strokes containing any errors are identified with a corresponding tag. Those tags are principally used to identify, on the server side of the project, the strokes containing errors, and to analyze them apart from the strokes that were performed correctly.

The purpose of the application's free drawing section is to assess the hypothesis that strokes that are not bound to follow specific rules like the ones used in the biomedical tests (start and stop in specific boundaries, start the stroke at a specific time, etc.) can also be used to analyze a user's biomedical parameters. In order to do that, the free drawing interface only presents a blank drawing area where the user is asked to draw triangles (Figure 1c). Since this shape is already used as a parameterized test, comparison between the data acquired by the triangle test and the data acquired with the free drawing test can provide useful insight on the validity of the free drawing data type. The rectangle or circle are other basic shapes that could also be incorporated to this application to be recognized and analyzed. We are considering a new function that could draw basic flow charts based on the recognition of a few of these basic shapes while at the same time recovering the necessary biomedical information. We may investigate this in the near future.

The data associated with the stroke is saved in an .hws file format which registers the timestamp, position, velocity and pressure of every data point. The velocity is estimated using Euclidian distance. All the meta-data associated with every stroke, such as an error occurrence and its type, are registered in a different text document. Those two files are then transferred from remote to central storage. The Advanced Encryption Standard (AES) encryption algorithm is also used to encrypt the data which must be kept private. The encryption process is password protected. The communication between the Google Drive, the tablet and the server is secured by using a special key that is associated with this specific application's account. This key is hard-coded in the tablet application and in the server.

4. Analysis of the data

This section presents the computation part of the project to analyze the data correctly. Firstly, when the encrypted .hws and text files are uploaded on the Google Drive account from the tablet, they are organized by user and type of test. Then, a distant server is used to fetch all new files and analyze them according to type. The second step is to decrypt the data so that it can be analyzed by the appropriate algorithm. Those algorithms are the Delta-lognormal and the Sigma-lognormal (Plamondon et al. 2009) that are used to respectively analyze the data from single strokes and from more complex strokes, such as the ones produced during the triangle shape test. The algorithms were conceived assuming the data acquired would be sampled at a frequency of 200Hz. This caused a problem with commercial tablets since the highest sampling frequency observed was 60 Hz and that frequency was not steady. To resolve this issue, a pre-processing step was added, by interpolating the data to simulate a 200 Hz frequency sampling. In the end, we want to be able to show the computed results on the tablet, which means going through the steps of re-encrypting the results from the analysis and transferring them from the server to the cloud.

One step must be added to properly analyze the data that is acquired during the free drawing test. The strokes must first be recognized as triangle-shaped before we try to analyze them in order to achieve the goal of validating the use of this kind of data. We use the Blurred Shape Model (BSM) descriptor, which is an improved version of the Zoning descriptor that encodes the probability of pixel densities of image regions (Escalera et al. 2009). This descriptor is computed on the image generated from the stroke that has been drawn on the screen, without taking into account the sampling and the speed. First, the image is divided into a grid of $n \times n$ equal-sized sub-regions. Then, each cell in the grid receives votes from the shape points in it and also from the shape points in the neighbouring sub-regions. Each shape point contributes to a density measurement of its cell and its neighboring cells. This contribution is weighted according to the distance between the point and the centroid of each region. Finally the descriptor is normalized within the range 0 to 1. In order to recognize the input symbol, the Euclidean distance is used to compute the similarity between the symbols stored in the database. Those symbols are specific to each user and are stored in the Google Drive cloud. Then, a k-Nearest Neighbour

algorithm is used for classification in order to differentiate different symbols such as rectangle and circles. This allows for further development of the application to recognize other shapes than the triangle. Finally, a second and a third classification processes are used to distinguish different types of triangles. Because the stroke order is important in the biomedical analysis, we make the distinction between the same symbols depending on whether they were drawn clockwise or counter-clockwise. The orientation of the stroke (clockwise/counter-clockwise) is determined using the formula [1]. The stroke orientation is determined by comparing whether the result is greater than 0. If this is the case, then the triangle was drawn clockwise; otherwise it was drawn counter-clockwise. This formula comes from the Shoelace formula for computing the area of a polygon. The constant factor from the Shoelace formula can be omitted since our sole interest is to compute the orientation and not the total area.

$$\text{Area} = \sum (x_{i+1}-x_i) (y_{i+1}+y_i) \quad [1]$$

The third classification process is useful for spatially locating the triangle's starting point. To classify the starting point of the triangle, nine different classes are used: up_left, up_centre, up_right, middle_left, middle_centre, middle_right, down_left, down_centre and down_right. This classification is performed by placing the point in a grid and analyzing where it is placed.

The BSM algorithm needs to be trained before the user draws the first free drawing strokes. The triangle biomedical test is used to accomplish that. In fact, if the user has not tried the triangle biomedical test before the free drawing program, they are automatically redirected towards the triangle biomedical test in order to train the recognizer. Once the training is done, the reference data is uploaded into their folder in the cloud and the user can use the application's free drawing test.

Once the data is analyzed, a new type of file with the results is created (.ana). Those results contain the lognormal parameters that model the velocity curves. For the Delta-lognormal algorithm, only one lognormal is sufficient to model the data while for the Sigma-lognormal algorithm, multiple lognormals are needed.

5. Conclusion

This work aims ultimately to produce a useful clinical tool that is able to detect early signs of specific diseases by analyzing handwriting-related data. The prototype presented in this paper supports the basic functionalities that we want to include in this work, such as the simple stroke and triangle shape tests. It also supports a more advanced function which is the detection of freely drawn triangles. Biomedical data is analyzed on a server in a secure way but the results still need to be interpreted and investigated.

A big issue with this process is its duration. Using a computer with low random-access memory for the server, the process of computing all the data to create a results file can take up to one minute. A substantial part of the processing time can be attributed to the booting of some programs needed by the lognormal algorithms. The processing time includes the time required for data transmission, but the transmission part of the process is insignificant (less than a second) compared to the computation time. In real-time mobile application, such a delay might create user dissatisfaction. Future optimization of the lognormal algorithms and a better understanding of the parameters useful in the interpretation of human movement might help reducing the processing time.

Overall, the goal was to create a working prototype – a goal which was successfully reached. All the steps were completed, from doing a test to receiving its results, the only downfall being the processing time, which can be easily improved by acquiring or designing an optimized server for the required calculations. Optimizing this delay is one of the requirements of being able to develop a large-scale application. A number of improvements can also be added to the application, such as a results window that interprets the analyzed data and the creation of experimenter accounts that would make it possible to change specific aspects of the application. The influence of the interpolated sampling frequency is also still yet to be evaluated. Interpreting the resulting data for neural pathology will be the final significant step in this work.

References

- O'Reilly, C., Plamondon, R. and Lebrun, L. H. (2014). Linking brain stroke risk factors to human movement features for the development of preventive tools. *Frontiers in aging neuroscience*, 6.
- O'Reilly, C. and Plamondon, R. (2011). Impact of the principal stroke risk factors on human movements. *Human movement science*, 30(4), 792-806.
- Plamondon, R., O'Reilly, C., Rémi, C. and Duval, T. (2013). The lognormal handwriter: learning, performing, and declining. *Frontiers in psychology*, 4.
- Plamondon, R., Djoua, M. and O'Reilly, C. (2009). La théorie cinématique des mouvements humains rapides: développements récents. *Traitement du Signal, Numéro Spécial : Le Document Écrit*, 26(5), 377-394.
- Escalera, S., Fornés, A., Pujol, O., Radeva, P., Sánchez, G. and Lladós, J. (2009). Blurred shape model for binary and grey-level symbol recognition. *Pattern Recognition Letters*, 30(15), 1424-1433.

A neurocomputational model of spinal circuitry for controlling the execution of arm voluntary movements

Antonio PARZIALE , Jacopo FESTA and Angelo MARCELLI
Natural Computation Laboratory
DIEM – University of Salerno
Via Giovanni Paolo II, 132
84084, Fisciano (SA), ITALY

Abstract. We present a model of the spinal cord in controlling one degree-of-freedom arm movements. The model includes both neural and musculoskeletal functions in an integrated framework. The model has been implemented by an artificial neural network coupled with a computational model of muscle publicly available. The experimental results show that the model is able to regulate the position of the arm and to mediate reflex actions by integrating commands from CNS and signals from proprioceptors.

1. Introduction

How voluntary movements of the arm are controlled by the brain is still an open question despite many studies on human movements have been conducted to give an answer to it. In recent years, the scientific community has realized that combining knowledge from behavioural studies, neurophysiological investigations and neural modelling is the right track to understand which processes occur within the central nervous system (CNS) and which is the role of the local circuitries in the spinal cord during the execution of a voluntary movement (Alstermark B. et al., 2007).

The neural structures involved in the control of movement can be roughly separated in four interconnected subsystems: the spinal cord system, the cerebral cortex and brainstem system, the cerebellum and the basal ganglia. Computational models of those systems, as for example (Contreras-Vidal et al., 1997; Stefanovic et al., 2014), are important because they allow to overcome the technical difficulties in monitoring the activity and the interactions of those system during normal tasks, so that physiological studies in human subjects are performed in controlled conditions, i.e. with the subject executes a reduced set of movements. Moreover, they allow to investigate pathways whose activities cannot be explored by other means.

In this study we present a neurocomputational model of the spinal cord and the way the CNS activates such a circuitry for controlling arm's movements.

2. The Spinal cord model

The spinal cord subsystem includes the alpha motor neurons, which innervate the skeletal muscle fibers with their axons, and interneurons that are the main targets of the projections coming from the upper centers and the major source of the alpha motor neurons. Moreover, the spinal cord hosts the gamma motor neurons, which innervate intrafusal fibers for keeping the muscle spindle sensitive to stretch.

The spinal cord receives motor commands from the brain motor areas and sensory afferents from spindles and tendon organs. As in part described by (Shadmehr et al., 2005), we hypothesized that, for each muscle, there are five supraspinal signals sent to the spinal cord: *Driving Signal (DS)*, *Length Control Signal (LCS)*, *Force Control Signal (FCS)*, *Gamma Static*, *Gamma Dynamic*.

The *DS* is the motor command used by the central system for selecting the muscle to be activated and for modulating force and velocity of the system.

The *LCS* is a descending input carrying information about the desired value of length for a given muscle and it is compared with the output of the II afferent fibers related to the homonymous muscle. When the output of the II afferent fibers is greater than *LCS* an excitatory synaptic input is sent to the alpha motoneuron and the innervated muscle is shortened.

The *FCS* is a descending input that sets the maximum allowable force that can be generated by the muscle and it is compared with the output of the Ib afferent related to the homonymous muscle. When the signal coming from the Golgi Tendon Organs is greater than *FCS* an inhibitory synaptic input is sent to the alpha motoneuron and the activation of the innervated muscle is reduced.

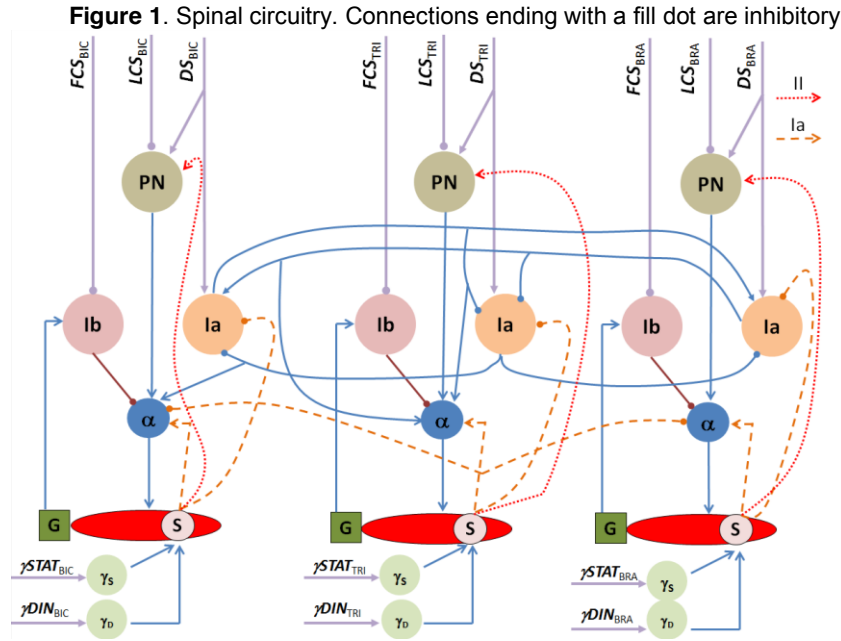
Gamma Static is used by the supraspinal system for modulating the output of primary and secondary afferent fibers, while *Gamma Dynamic* is used for modulating the output of the primary afferent fibers.

The spinal networks of the prime-mover muscle and of its synergist and antagonist muscles are interconnected in order to locally regulate the operating point of the system. The interconnections have been partially derived from physiological and anatomical studies (Pierrot-Deseilligny and Burke, 2005) and are reported in Figure 1. In this study, a simple model has been adopted for each neuron, in particular the axonal output is equal to:

$$y = 1/(1 + e^{-a(\sum_i x_i w_i + b)}) \quad (1)$$

where x_i is the i -th synaptic input, and w_i is the related weight that could be positive or negative depending on whether the input was excitatory or inhibitory, a is the gain and b is the bias. Given the network in Figure 1, we need to compute 64 parameters in order to define the transfer function of each neuron. To simplify the problem, we hypothesized that each parameter assumes the same value for all the neurons belonging to the same class (i.e. Ib neurons, Ia neurons, etc.), so that the number of unknown parameters dropped to 21. We used a Hill Climber/Steepest Descent algorithm for finding the set of parameters that satisfy the following requirements:

- a relation between the *Driving signal* and the axonal output of the alpha motoneuron as linear as possible;
- if the signal from the Ib afferent fiber is smaller than the *FCS* the axonal output of the Ib inhibitory interneurons must be almost 0, otherwise it must increase with a slope equal to $1/(1-FCS)$.



2.1 The musculoskeletal model

The musculoskeletal model used in this study is a one degree-of-freedom arm whose motion is restricted to the extension/flexion of the elbow. In fact, the shoulder and the wrist joints are grounded while the elbow joint is modelled as a hinge-like joint. The skeleton is made up of four bones: humerus, ulna, radius and hand. The physical parameters used for the bones are reported in Table 1.

Table 1 Bones physical parameters

	<i>Mass</i>	<i>Length</i>
Humerus	350 g	28 cm
Ulna	200 g	22 cm
Radius	200 g	23 cm
Hand	500 g	-

The musculoskeletal model includes three muscles: Biceps Short, Brachialis and Triceps Long. We chose to use Virtual Muscle (Cheng et al., 2000; Song et al., 2008) as muscle model, which combines the advantages of phenomenological (Hill-type) and mechanistic (Huxley-type) models. In particular, Virtual Muscle groups a set of phenomenological models, each of which describes the processes involved in muscle contraction. It is needed to specify a set of parameters for each muscle model: the properties of individual fiber type are reported in (Cheng et al., 2000) whereas the morphometric parameters are reported in Table 2.

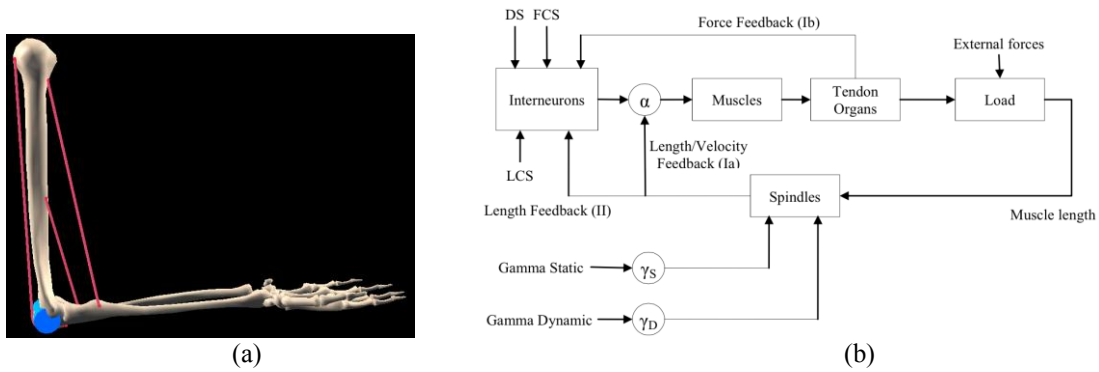
Table 2 Muscles physical parameters. In the last column S means *Slow* and F means *Fast*

	<i>Opt. Fascicle Len.</i>	<i>Opt. Tendon Len.</i>	<i>Max. Musculotendon Len</i>	<i>Mass</i>	<i>Fibers Type</i>
Biceps	14.75 cm	7.4 cm	32 cm	350 g	40% S., 60% F.
Brachialis	10 cm	3 cm	18 cm	300 g	60% S., 40% F.
Triceps	19.9 cm	9.9 cm	36 cm	500 g	60% S., 40% F.

Force and metabolic energy consumption are estimated by the model in response to neural excitation, muscle length and velocity (Tsianos et al., 2012). Virtual Muscle is equipped with realistic models of spindles (Mileusnic et al., 2006) and Golgi tendon organs (Mileusnic et al., 2006b) that respond, respectively, to muscle stretch and fusimotor control and to muscle tension. The spindle provides information about the rate of muscle length change and muscle length through Ia (primary) afferent fibers, and information about the muscle length through II (secondary) afferent fibers. Golgi tendon organs provide information about the force produced by the muscle during his contraction through Ib afferent.

Eventually, a cylindrical wrapping object is used to model the bony surfaces over which the triceps muscle wrap. It ensures the right calculation and application of the muscle forces produced by the muscle on the skeletal system. The arm model has been developed in the MSMS simulator (Khachani et al., 2008) and it is depicted in Figure 2.a, while Figure 2.b illustrates the connections between the supraspinal systems, the spinal cord, the muscles, the proprioceptors and the environment.

Figure 2. : (a) The arm model. Muscles are represented in red, the wrapping object is in blue. (b) The spinal circuitry block diagram



3. Experimental results

As validation, we arranged three experiments to verify if the arm movement was appropriate when an external force or a load was applied and if the spinal cord model was able to control the musculoskeletal model for reaching a desired position.

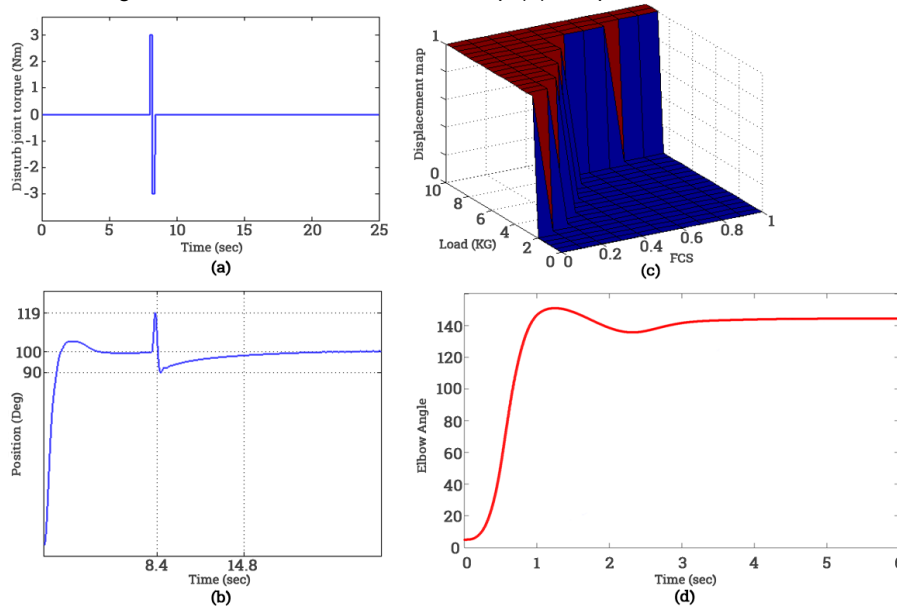
The *first experiment* verified if, without variations of the motor commands sent by CNS, the spinal circuitry was able to keep the position of the arm when the impulsive external force depicted in Figure 3.a was applied. A similar experiment was carried out on deafferented monkeys to evaluate the role of spinal cord in the execution of a movement (Shadmehr et al., 2005). As shown in Figure 3.b, at the beginning the elbow was moved from the initial position $\theta=5^\circ$ to the desired position $\theta_D=100^\circ$ and then, after some seconds, the impulsive force was applied. The elbow angle showed an overshoot of 17.2° and an undershoot of 7.8° but after a recovery time equal to 4.8 seconds the desired angle was reached again. The same experiment was performed for different desired positions and the spinal circuitry was always able to keep the position after a mean recovery time equal to 1.19 seconds, a mean overshoot of 4.2° and a mean undershoot of 3.7° . By varying the values of *Gamma Dynamic* signals it was possible to regulate the response of the system (unpublished results).

The aim of the *second experiment* was to verify if the protective mechanism of the Golgi reflex was implemented by the presented spinal circuitry and if it could be modulated by varying *FCS*. The arm was placed at the position $\theta=100^\circ$ and then the *FCS* value of each muscle and the external weight loaded on the hand were modified. In particular, each muscle received the same *FCS* that was varied from 0 to 1 with a step size of 0.1 while the weight was varied from 0 Kg to 10 Kg with a step size of 0.5 Kg. Given a value for *FCS* and for the weight, we evaluated if the arm kept the initial position or not. In Figure 3.c a displacement map is reported and the displacement was set to 0 if the arm kept the initial position, it was set to 1 otherwise. It resulted that the bigger was the weight the bigger had to be *FCS* for keeping the position of the arm. It follows that *FCS* can be used to regulate the threshold of the Golgi reflex.

Eventually, the aim of the *third experiment* was to verify if it was possible to control the arm in order to reach a desired position in a suitable time. We chose to model each *driving signal* with a square burst for which three parameters had to be specified: the duration t , the amplitude A and the steady state value E . The last two parameters range between 0 and 1 and both modulate the firing frequency of a motor unit. For the sake of simplicity, we hypothesized that each burst had amplitude A equal to 1, the bursts sent to the agonist muscles had the same duration $t_{AGONISTS}$, the steady state value was equal to $E_{AGONISTS}$ for biceps and brachialis and it was equal to 0 for the triceps because its effect can be taken into account, in first approximation, with the effect of the

gravity. Therefore, the problem was reduced to find the parameters $E_{AGONISTS}$, $t_{AGONISTS}$, $t_{ANTAGONIST}$ for each direction. For example, the desired position $\theta_D=140^\circ$ was reached setting $E_{AGONISTS}=0.40$, $t_{AGONISTS}=0.40$ seconds, $t_{ANTAGONIST}=0.10$ seconds, as shown in Figure 3.d.

Figure 3. (a) External force applied to the arm (b) Position of the arm before and after the external force (c) Effect of the Golgi Reflex when the arm lifts a load up (d) Response of the arm for reaching 140 deg.



4. Conclusions

We have presented a model of human spinal cord that was able to regulate the position of a 1-DOF arm by integrating commands from CNS and signals from proprioceptors. The experimental results confirmed that the presented spinal cord circuitry is able to mediate the same reflex actions showed by the human. Furthermore, the CNS is able to control the arm position by modulating the duration and the amplitude of the driving signals sent to spinal cord circuitry. Nevertheless, as shown in Figure 3.d, a desired arm position is reached in a time that is slower than the time spent by a human to perform the same movement. The slowness of the system is due to the simple scheme adopted to modulate the three driving signals, and therefore, in the future, we will investigate the behaviour of the system when a different time evolution for the five control signals is adopted. Eventually, the realism of the simulated system will be evaluated with other experiments, as for example by verifying that simulated movements show a velocity profile that fits the real one.

References

- Alstermark, B., Lan, N., Pettersson, L. (2007). Building a realistic neuronal model that simulates multi-joint arm and hand movements in 3D space, *HFSP Journal*, Vol. 1, No. 4, pp. 209-214
- Contreras-Vidal, J.L., Grossberg, S., and Bullock, D. (1997). A neural model of cerebellar learning for arm movement control: Cortico-spino-cerebellar dynamics. *Learning and Memory*, 3, pp. 475-502.
- Stefanovic, F., Galiana, H.L. (2014) A Simplified Spinal-Like Controller Facilitates Muscle Synergies and Robust Reaching Motions, *IEEE Trans Neural Syst Rehabil Eng.*, vol.22, no.1, pp.77,87,
- Shadmehr, R., Wise, S.P. (2005). The computational Neurobiology of Reaching and Pointing, MIT Press
- Pierrot-Deseilligny, E., Burke, D. (2005). The circuitry of the Human Spinal Cord: its role in motor control and movement disorders, Cambridge University Press, ISBN: 13978-0-521-82581-8
- Cheng, E.J., Brown, I.E., Loeb, G.E. (2000). Virtual Muscle: a computational approach to understanding the effects of muscles properties on motor control, *Journal of Neuroscience Methods*, Vol. 101, pp. 117-130
- Song, D., Raphael, G., Loeb, G.E. (2008). Computationally efficient models of neuromuscular recruitment and mechanics, *Journal of Neural Engineering*, Vol. 5 n^o2, pp. 175-184
- Tsianos, G.A., Rustin, C., Loeb, G.E. (2012). Mammalian muscle model for predicting force and energetics during physiological behaviors., *IEEE Trans Neural Syst Rehabil Eng* 20, pp.117-133.
- Mileusnic, M.P., Brown, I.E., Lan, N., Loeb, G.E. (2006). Mathematical Models of Proprioceptors. I. Control and Transduction in the Muscle Spindle, *Journal of Neurophysiology*, Vol. 96, pp. 1772-1788
- Mileusnic, M.P., Brown, I.E., Loeb, G.E. (2006b). Mathematical Models of Proprioceptors. II. Structure and Function of the Golgi Tendon Organ, *Journal of Neurophysiology*, Vol. 96, pp. 1789-1802
- Khachani, M., Davoodi, R., Loeb, G.E. (2008). Musculo-skeletal modeling software (MSMS) for biomechanics and virtual rehabilitation, Alfred Mann Institute and Department of Bionedical Engineering, USC, USA.

Handwriting Analysis with Online Fuzzy Models

Manuel BOUILLON^a and Eric ANQUETIL^a

^a *INSA Rennes, Avenue des Buttes de Coesmes, F-35043 Rennes*
IRISA, CNRS UMR 6074, Campus de Beaulieu, F-35042 Rennes
Université Européenne de Bretagne, FRANCE
{manuel.bouillon, eric.anquetil}@irisa.fr

Abstract. This paper presents the early work, done in the context of the IntuiScript project, on handwriting quality analysis. This IntuiScript project aims at developing a digital workbook to help with teaching children how to write. To do so, we must be able to analyse their handwriting, to evaluate if the letters are correctly written, and to detail what aspects of the child symbols – letters, numbers, and geometric forms - do not correspond to the teacher models. We use an online fuzzy model to easily build target models, and to automatically evaluate the adequacy of children letters to these reference models, with respect to different aspects: symbol shape, drawing direction and stroke order for example.

1. Introduction

This paper presents the early work, done in the context of the IntuiScript project (<http://intuiscript.com/>), on handwriting quality analysis. As opposed to symbol recognition, where one wants to assign a label to unknown characters, we want here to analyse how a known character fits its label model, in term of shape, direction, stroke order, speed, fluidity, etc.

This IntuiScript project aims at offering an advanced digital writing learning experience at school by using tablet and tactile digital devices (with finger touch and stylus). The objective is to develop a digital workbook for teaching literacy to children between 3 and 7 years old. We especially focus on teaching how to properly form and write cursive letters (Falk et al, 2011). The main advantage that the IntuiScript project brings is ideally improving current educational practices by providing digital learning tools that can be modelled by the teacher and customized according to each student learning progress. The project is backed up by an educational team representing the whole region of Brittany (5 million population), and 1,000 primary school students from Brittany will participate in the project experimentation. Figure 1 shows a first application to create writing exercises and analyse drawn symbols.

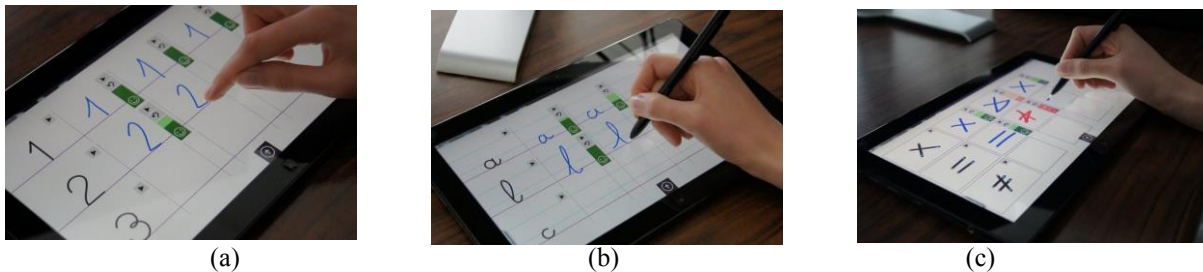


Figure 1: Illustration of the concept of writing quality automatic evaluation.

The problem we tackle here is to quantitatively evaluate a cursive symbol with respect to a reference model (Kulesh et al, 2001; Li-Tsang et al, 2013). In order to be able to teach children how to write, we must be able to analyse their handwriting, to evaluate if the letters are correctly written, and to detail what aspects of the child letters do not correspond to the teacher models. This problem is completely different from the classical task of character recognition, where the challenge is to determine to which class data samples belongs. In our case, we already know data labels, because children were asked to draw a specific letter, but we want to evaluate how close is this drawn letter to the reference model, and for which aspects it does not.

Our objective is to be able to analyse and evaluate handwritten symbols, with regards to reference models, and for multiple aspects. A correctly handwritten gesture is characterised by several aspects: first its shape, but also its drawing direction and order, its speed and its fluidity for instance. For each these aspects of the analysis, we use a specific feature set, specially designed to capture the desired aspect. In this paper, we present three different feature sets define a priori to analyse three aspects: the shape, the order and the direction. With those feature sets, we use an analysis system we built from an evolving fuzzy classifier. It allows to easily define reference models from few data samples to customize the writing exercises to the children. Then, the analysis system can be used to evaluate drawn gestures, regarding a specific feature set, and finally give a confidence score, regarding the specific aspect of the feature set.

This paper is organized as follows. Next Section briefly presents the Fuzzy Inference System we use to recognize and analyse cursive letters. Section 3 details the features and the confidence measure we use to

evaluate writing quality with respect to the teacher models. Section 4 shows qualitative examples and experimental results. Finally, Section 5 concludes this paper and presents future work.

2. Evolving Fuzzy Inference System

In this section, we present the architecture of the evolving Fuzzy Inference System named Evolve (Almaksour and Anquetil, 2011) that we use to analyse children handwriting. This system is derivable to obtain different specific analysis, with respect to various criteria, as we will detail in Section 3.

The system we use to analyse handwriting is an evolving Fuzzy Inference System, which was originally designed for online characters recognition. It can start learning from few data and then learns incrementally in real time from the run-time data flow, to adapt its model and support class adding during its use. We take advantage of these characteristics to design our handwriting analysis system. The fact that very few data are required to initialise the system, two or three samples per class, allows the teacher to easily define personalized exercises for each pupil. In the same way, new exercises with new classes, new letters/numbers/symbols, can easily be added at run-time. The evolving nature of the system allows to incrementally learn the specific model of the child handwriting as it improves. It enables to observe children progresses, by watching their models becoming closer to the teacher reference model.

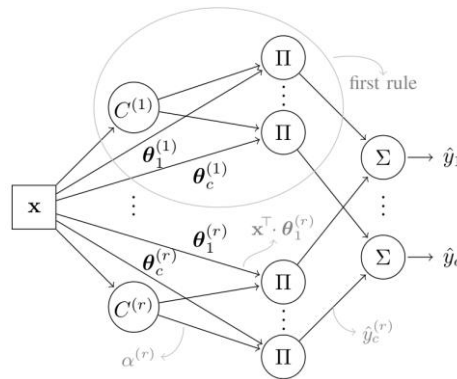


Figure 2: The fuzzy analysis system displayed as a neural network.

A fuzzy inference system is a set of fuzzy if-then rules. Rule premises are membership to clusters of the feature space. Those clusters ($C^{(i)}$) model the data distribution, each cluster represents the prototype of a symbol class (y_i). The premises can easily be used to evaluate the adequacy of a symbol to existing class models. Rule conclusions are linear functions ($\theta_1^{(i)}$) of the input (x) that give membership degrees to all classes (y_1, \dots, y_c). Those linear functions allow to improve the discriminative power of the system by increasing the precision of the class fuzzy boundaries between the prototypes. The conclusions can also be used to evaluate the difference between a symbol and existing classes.

3. Confidence Measure and Feature Sets

In order to compare a letter sample to the reference model, a common approach is to use the recognition confidence as a quality measure (Gao et al, 2011). To be more precise, we use here a compound measure that fuses information from two inner measures: an absolute and a relative confidence measure. The absolute confidence measure evaluates the similarity between a data sample and system corresponding model, and allow to measure data resemblance to expected symbol.

$$\text{absolute_confidence}(x^{(k)}) = 1/(1+\text{mahalanobis_distance}(x^{(k)}, C^{(k)})) \quad (1)$$

The relative confidence measure enables to assess system confusion between the different models, and can be used to evaluate data difference to other symbols.

$$\text{relative_confidence}(x^{(k)}) = (y^{(k)} - \max(y^{(p)}, p \neq k)) / \max(y^{(p)}, p \neq k) \quad (2)$$

Both aspects are complementary in the analysis of handwriting, characters have to as close as possible to the reference model, and as different as possible to other models of different symbols. We fuse both measures to take advantage of both aspects in our analysis.

This work is based on the Heterogeneous Baseline Feature Set HBF49 (Delaye and Anquetil, 2013), which is a unified feature representation for universal online symbol recognition. This feature set aims at being the most general and multi-purpose possible, it is able to describe any kind of symbol, either single stroke or multi-stroke. In particular, some of its features are sensitive to orientation and stroke order, which is very interesting for handwriting quality analysis. HBF49 is an excellent baseline to analyse cursive symbols from a general point of view, it gives a synthetic score representing the general quality.

In order to be able to evaluate handwritten symbols with regards to different aspects, we selected a priori some specific features from HBF49 to allow a precise analysis of some particular aspects of the handwritten symbols. A first specific feature set (FS 1), that contains symbol length, bounding box angle and zoning features, was designed to evaluate symbol shapes. A second (FS 2), containing extremities coordinates, the initial angle and the first to last point vector, was designed to assess symbol stroke drawing order. Finally, a last feature set (FS 3) was designed, with the down stroke proportion, the average direction and the absolute and relative orientation histograms, to estimate symbol drawing direction. Table 1 summarized feature sets composition, using HBF49 feature numbering.

Feature Set	Features
HBF49	F1 to F49
FS 1 (shape)	F15, F16, F17, F32 to F40
FS 2 (order)	F1 to F7
FS 3 (direction)	F13, F24 to F31

Table 1: HBF49 features used in the specific feature sets.

4. Experimentation

This Section presents the first experimental results that we obtained with our method, and our three specific features sets, to analyse handwritten symbols.

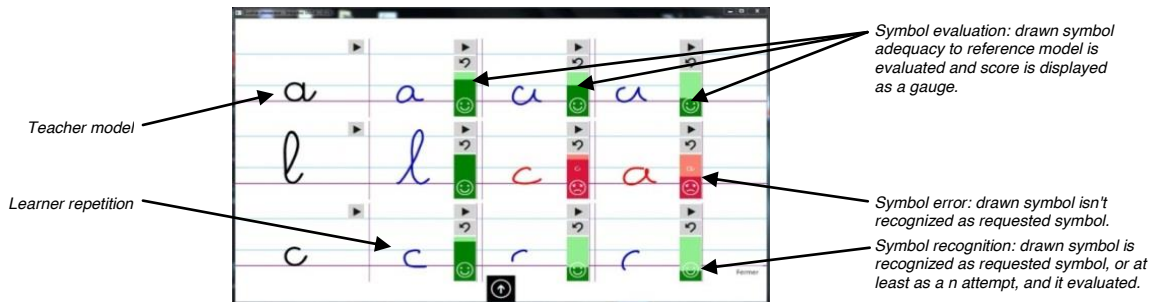


Figure 3: Global analysis score (using HBF49 only).

Figure 3 shows a screenshot of our demo application, for the IntuiScript project, that provide a global analysis score using the HBF49. One can see on the first and third lines that the global score decreases as the letters deteriorates. The second line shows a red feedback when symbols are not recognized as the one that was asked.

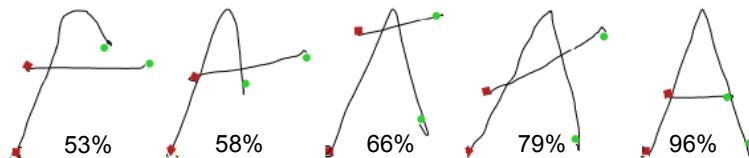


Figure 4: Confidence values for FS 1 (shape) for some 'A' samples.

Figure 4 presents the evolution of the shape sensitive score obtained with the first specific feature set. The obtained quality measure is shape sensitive, but indifferent to drawing direction or stroke drawing order for example. As a result, the computed score only depends on the symbol shape, and increases as the shape improves and moves closer to the teacher model. This evolution shows the effectiveness of our shape oriented measure to rank poorly drawn symbols.

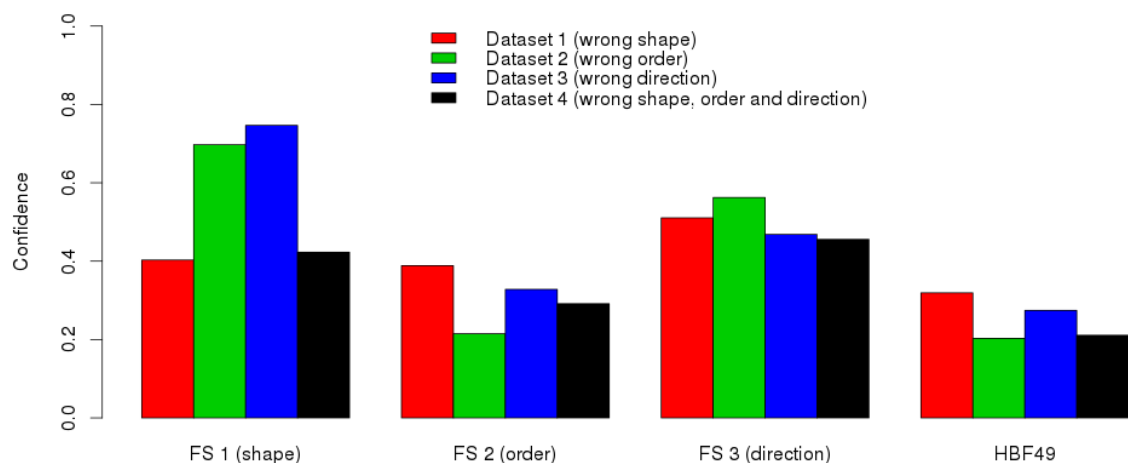


Figure 5: Confidence of each feature set for the four datasets.

Finally, Figure 5 is a plot of the different evaluation scores obtained with the three specific feature sets and HBF49, for four different datasets. First dataset contains badly shaped data samples. The second dataset contains goodly shaped symbols, but with wrong drawing orders. The third dataset contains data samples that were drawn in wrong directions. Finally, the fourth data set comprises various symbols with at the same time a wrong shape, incorrect drawing order and drawing directions.

As a result, the averaged evaluation score obtained with the first feature set, sensitive to shape, is low on the first and last datasets, but quite high on the second and third. Similarly, the drawing order oriented feature set yield poor scores on the second and last datasets, but better scores on the first and third. Finally, the feature set evaluating the drawing direction gives lower scores on the two last datasets than on the two first. This experiment highlights the specificity of each feature set on the corresponding datasets, and demonstrates the effectiveness of our method to evaluate handwritten symbols quality regarding different criteria.

5. Conclusion

This paper has presented a new method to evaluate handwritten symbols, letters as well as numbers or any geometric form, with the help of online fuzzy models. Those reference models can easily be customized by the teacher to adapt to the child difficulties.

Our method takes advantage of our fuzzy inference system generative and discriminative capacities to evaluate handwritten symbols, with respect to the used feature set. We have presented here three specific feature sets to analyse symbol shape, drawing order and direction. Additionally, various other feature sets can be designed to analyse cursive writing with other criteria using our method.

Future work will focus on designing several other features and feature set to widen the quality analysis we are able to perform. In particular, we plan to investigate automatic feature selection algorithm to fasten and improve feature set design.

References

- Almaksour, A., Anquetil, E., 2011. Improving premise structure in evolving Takagi-Sugeno neuro-fuzzy classifiers. *Evolving Systems* 2, 25–33. doi:10.1007/s12530-011-9027-0
- Delays, A., Anquetil, E., 2013. HBF49 feature set: A first unified baseline for online symbol recognition. *Pattern Recognition* 46, 117–130. doi:10.1016/j.patcog.2012.07.015
- Falk, T.H., Tam, C., Schellnus, H., Chau, T., 2011. On the Development of a Computer-based Handwriting Assessment Tool to Objectively Quantify Handwriting Proficiency in Children. *Comput. Methods Prog. Biomed.* 104, e102–e111. doi:10.1016/j.cmpb.2010.12.010
- Gao, Y., Jin, L., Li, N., 2011. Chinese handwriting quality evaluation based on analysis of recognition confidence, in: 2011 IEEE International Conference on Information and Automation (ICIA). pp. 221–225. doi:10.1109/ICINFA.2011.5948991
- Kulesh, V., Schaffer, K., Sethi, I.K., Schwartz, M., 2001. Handwriting Quality Evaluation, in: *Proceedings of the Second International Conference on Advances in Pattern Recognition, ICAPR '01*. Springer-Verlag, London, UK, UK, pp. 157–165.
- Li-Tsang, C.W.P., Wong, A.S.K., Leung, H.W.H., Cheng, J.S., Chiu, B.H.W., Tse, L.F.L., Chung, R.C.K., 2013. Validation of the Chinese Handwriting Analysis System (CHAS) for primary school students in Hong Kong. *Research in Developmental Disabilities* 34, 2872–2883. doi:10.1016/j.ridd.2013.05.048

Evaluation of Different Handwriting Teaching Methods by Kinematic and Quality Analyses

Pierluigi D'ANTRASSI ^a, Paola CESCHIA ^b, Carmen MANDARINO ^b, Iolanda PERRONE ^c and Agostino ACCARDO ^a

^a *Dept. of Engineering and Architecture, University of Trieste, 34127, Via Valerio, 10, Trieste (TS), ITALY*

^b *Primary School, Don Milani, Via Don Milani, 4, 20063, Cernusco sul Naviglio (MI), ITALY*

^c *Department of Development Age, ULSS 7, Via Lubin, 16, 31053, Pieve di Soligo (TV), ITALY*
pierluigi.d'antrassi@phd.units.it, accardo@units.it

Abstract. Handwriting difficulties represent a common cause of underachievement in children education and low self-esteem in daily life. The analysis of handwriting could be an important tool for the evaluation of a teaching method in order to assess its efficacy in preventing dysgraphia. We performed a comparative analysis of the traditional handwriting method and the alternative Terzi's approach in pupils at the end of primary school, when cursive skills should have been achieved.

Qualitative and kinematic parameters were considered: the first ones were calculated as a visual analysis of written texts (by using check-lists and scales regarding qualitative, postural and pen grasp aspects), while the latter ones were automatically extracted through digitizing tablet acquisitions. Results showed significant differences concerning handwriting quality and dynamic movement in pupils handwriting depending on the teaching method applied.

1. Introduction

A large number of school-aged children have difficulties with handwriting. Dysgraphia is one of these: it consists in a learning disability that often involves a written illegible product. Problems like this can affect not only their self-esteem, but also their school performance and everyday life in the future. (Losse & al., 1991; Skinner & al., 2001; Cummins & al., 2005).

The increase in worldwide percentage of children with writing difficulties may be caused by: increasing use of modern technologies (Sülzenbrück & al., 2011); lacking cursive instruction for elementary school students (Hanover Research, 2012); inappropriate teaching methods and failure to detect child's difficulties (Martins & al., 2013). In order to evaluate teaching methods and identify handwriting problems like dysgraphia, the approach usually performed includes two different analysis. The first one is related to digitally recorded writing samples, using characteristic parameters that measure the specific kinematic features (Accardo & al., 2014); the second one is a visual analysis of the written product for a qualitative evaluation of handwriting goodness (Genna et al., 2015).

In this paper, involved teaching handwriting methods are the traditional ones and the Terzi's approach (Terzi, 1995). Ida Terzi was a primary school teacher at the institute of blind people in Reggio Emilia, Italy, in the first half of the 1900s. She proposed a space-time method which aim was to develop students' perception of the body moving in space. Information from personal (body perception), peri-personal (objects manipulation) and extra-personal (environment) spaces are mixed up in order to facilitate perceptual consistency and transition from unconscious to conscious use of the body in motion. In Terzi's approach blindfolded pupils experience on the wall the graphic symbol with large movements of the arm and hand by their teacher aid; then they independently reproduce the motor representation on the wall and at a later stage on large sheets with brush and colour, shifting from a vertical plane to a horizontal one. At last, letters are reproduced, with decreasing size, in elliptical patterns, in squares of 0.5 cm and finally in ruled paper of their specific classes. Instead, in the traditional handwriting programs, instructions about letters formation take place as a group activity rather than as an individualized one. Teacher requires children to observe from blackboard or books the shape of letters, to remember them, and to transfer on their copybook what their visual memory stored.

The aim of this work is to compare the traditional way to teach writing with the experimental space-time method of Ida Terzi during the last year of primary school, when cursive skills should have been achieved.

2. Materials and methods

Participants. The present study provides the enrollment of 20 pupils (7 male and 13 female) for each classroom and therefore for each teaching handwriting method: the "Don Milani" primary school of Cernusco sul Naviglio, that follows the Ida Terzi's method (experimental group labelled with CE) and the primary school of Pioltello, that instead uses the traditional teaching method (control group, labeled with PI). The analysed acquisitions were made at the end of the 5th grade, the last year of cursive handwriting classes. All subjects were Italian mother-tongue, right-handed, with no handwriting problems or organic pathologies, and belonging to the same area with medium socioeconomic status.

Tests. Kinematic and qualitative handwriting evaluations were mainly based on two tests that require

adequate linguistic competences and cursive writing skill. These tests consist in writing in accurate (A test) and in fast (F test) mode the following Italian sentence: *In pochi giorni il bruco diventò una bellissima farfalla che svolazzava sui prati in cerca di margherite e qualche quadrifoglio* (meaning “In a few days the caterpillar became a beautiful butterfly fluttering on the lawns in search of some daisies and clover”). This sentence was constructed with the aim of containing all the letters of the Italian alphabet and several phonological rules.

Processing and statistical analysis. In order to evaluate differences between the two teaching methods, qualitative and kinematic parameters were separately processed for each test.

Hand-motor performance quantification was undertaken with special regard to the basic writing elements: strokes and components assessment (Van Galen, 1998). A proprietary MATLAB program (Genna & al., 2011) was used to perform this analysis. Strokes were identified as segments between points of minimal curvilinear velocity, as suggested by the bell-shaped velocity profile theory (Djioua, 2009). Components were identified as the written tracts between two consecutive pen lifts.

In order to provide information on the level of automation and fluency achieved by a child, a series of kinematic and static parameters were calculated and analysed for each test (Rosenblum, 2006): duration, length, mean and peak of curvilinear, horizontal and vertical velocity evaluated for the whole written track, components and strokes; pen lift duration; number of components, strokes and letters per second and per unit space.

About qualitative analysis, a manual approach was used (Genna & al., 2015): an evaluation scale based on a new neuromotor model of handwriting production. In order to define the TQs (total quality scores), the ratio between the number of errors made and the maximum number of the possible ones for each parameter was evaluated. In addition, this normalized scores was weighed through the AHP method to guarantee an objective evaluation of handwriting goodness.

For both qualitative and kinematic parameters, the significance of difference between PI and CE group score was evaluated by means of the Wilcoxon test for independent samples. In order to identify the most significant parameters, in terms of difference between groups, stepwise regression with forward selection was used in both A and F tests.

3. Results and discussion

Results were obtained from kinematic and qualitative analysis: the writing process is "stressed out" to evaluate the speed of handwriting and the quality of the graphics performance.

Kinematic analysis. Starting from the digitally recorded writing samples of each student, kinematic and static parameters, relative to the whole written track and its components and strokes, were estimated. The first step has been the evaluation of the statistically significant differences (p -values <0.05) between results of two groups arising from the application of the Wilcoxon test for independent samples.

Table 1. Mean \pm 1SD of most significant full track parameters calculated in both A and F test for CE and PI groups.

Track Parameters	A test			F test		
	CE	PI	p-value	CE	PI	p-value
Whole duration (s)	97 \pm 16	128 \pm 28.3	$< 0,0001$	74.4 \pm 11.5	76 \pm 9.4	n.s.
Whole length (mm)	1262.8 \pm 223.2	1451.8 \pm 205.4	$< 0,02$	1365.3 \pm 269.3	1505.9 \pm 239.6	n.s.
Curvilinear vel (mm/s)	18.6 \pm 4.7	21 \pm 6.7	n.s.	25 \pm 5.2	32.9 \pm 6.2	$< 0,0002$
Horizontal vel (mm/s)	8.9 \pm 2.3	10.9 \pm 3.8	n.s.	12.4 \pm 2.5	17.8 \pm 4.1	$< 0,0001$
Vertical vel (mm/s)	13.9 \pm 3.9	14.8 \pm 4.7	n.s.	18.1 \pm 4.3	22.3 \pm 4.4	$< 0,004$
Whole pen lift durm. (s)	28 \pm 9.1	55 \pm 17	$< 0,0001$	19.2 \pm 6	30 \pm 8.5	$< 0,0002$
#Components	57.4 \pm 17.3	103.8 \pm 21.7	$< 0,0001$	55.7 \pm 17.6	97.1 \pm 20	$< 0,0001$
#Strokes	431.2 \pm 41.7	485.7 \pm 85.8	n.s.	381.4 \pm 43.1	365.8 \pm 40	n.s.
#Components/#Letters	0.5 \pm 0.2	1 \pm 0.2	$< 0,0001$	0.5 \pm 0.2	0.9 \pm 0.2	$< 0,0001$
#Strokes/#Letters	4 \pm 0.3	4.5 \pm 0.8	n.s.	3.6 \pm 0.4	3.4 \pm 0.3	n.s.
#Letters/cm	0.89 \pm 0.15	0.76 \pm 0.1	$< 0,01$	0.81 \pm 0.15	0.73 \pm 0.12	n.s.
#Letters	108.8 \pm 3.4	107.8 \pm 0.5	n.s.	107.1 \pm 4.2	106.7 \pm 3.2	n.s.

In fast modality, the two groups use the same time to write the sentence. The control group (PI) is significantly faster with the pen on the paper than CE group but spend more time during pen lift.

In accurate modality, the experimental group (CE) ends the test in less time than PI. The control group finds greater difficulty in accurate writing indeed they spend significantly more time during pen lift respect CE group and respect itself in the fast modality.

A greater pen lift duration is related to a bigger number of components and, as the number of letters is the same between groups, it entails a higher level of fragmentation in letters execution (#Component/#Letters) for the control class. Components are the written tracts between two consecutive pen lifts, therefore the minimum number expected is equal to the number of words plus the number of “i”, “t”, “z”, “ò”, that is, those characters which need a pen lift for their completion (in our sentence the minimum #Components is 40).

Kinematic analysis shows that PI students need more time to organize the graphomotor task (greater pen lift) and struggling more to tie together the letters smoothly (using one component per letter). CE students spend less time during pen lift because they have successfully automated the graphomotor process and the ligation process between letters (on average, one component every two letters).

By means stepwise regression was possible to detect the most significant parameters for both tests: *number of components* and *strokes* for A test and *mean length*, *mean vertical velocity* and *mean horizontal ascendant velocity of components* for F test.

Qualitative analysis. A similar analysis was performed on the 16 qualitative parameters in terms of TQS (Genna & al., 2015). Table 2 represents the most statistically significant parameters in which the two schools was compared. The p-values indicate significance of the difference between samples in terms of error rate.

Table 2. Mean±1SD of most significant qualitative parameters (TQs) calculated in both A and F tests for each sample. a: posture area; b: handgrip area; c: sheet graphic space area; d: row graphic space area; e: graphomotor patterns area

	A test			F test		
	CE	PI	p-value	CE	PI	p-value
Total error score	0.076±0.016	0.116±0.023	< 0.0001	0.082±0.02	0.354±0.086	< 0.0001
a.1. Inefficient posture	0.004±0.006	0.009±0.005	< 0.003	0.004±0.006	0.009±0.005	< 0.003
b.2. Inefficient handgrip	0.015±0.011	0.027±0.013	< 0.005	0.015±0.011	0.027±0.013	< 0.005
c.1. Variability of the left alignment	0.001±0.003	0.001±0.004	n.s.	0.001±0.004	0.013±0.007	< 0.0001
d.1. Irregular word spacing	0.008±0.009	0.015±0.011	< 0.03	0.007±0.008	0±0	< 0.0001
d.2. Letter collisions	0.001±0.002	0.001±0.001	n.s.	0.002±0.002	0.021±0.015	< 0.0001
d.3. Max variation of letter size	0.022±0.007	0.028±0.008	< 0.02	0.023±0.009	0.001±0.001	< 0.0001
d.4. Wrong letter size	0.005±0.002	0.006±0.003	n.s.	0.004±0.002	0.11±0.043	< 0.0001
e.1. Wrong graphomotor pattern	0.008±0.006	0.013±0.007	< 0.02	0.01±0.008	0±0	< 0.0001
e.2. Dysmetria in letters execution	0.003±0.003	0.007±0.005	< 0.007	0.004±0.004	0.014±0.008	< 0.0001
e.3. Self-corrections of grapheme written	0±0.001	0±0	< 0.003	0±0.001	0.121±0.041	< 0.0001

Total error score of PI group is higher (then worst) than CE group for both accurate and fast modalities of execution in the handwriting context. Comparing the two tests, the experimental group obtained almost the same total quality score; unlike the control group has a slightly greater number of errors switching from accurate modality to the fast one. It is useful to observe the single sub-areas, and then their relative sub-criteria, to better understand the specific differences between the two groups.

About peripersonal space, CE group keeps a better posture and handgrip than PI group.

In accurate modality, other significant differences between CE and PI group are present in the *row graphic space* and *graphomotor patterns* areas. Indeed, CE group keeps a more regular word spacing, a better letter size uniformity, more correct graphomotor patterns and less dysmetria in letters execution. Besides that, switching to F test, more significant differences are detected. Increasing handwriting speed, PI group makes more errors unlike CE group.

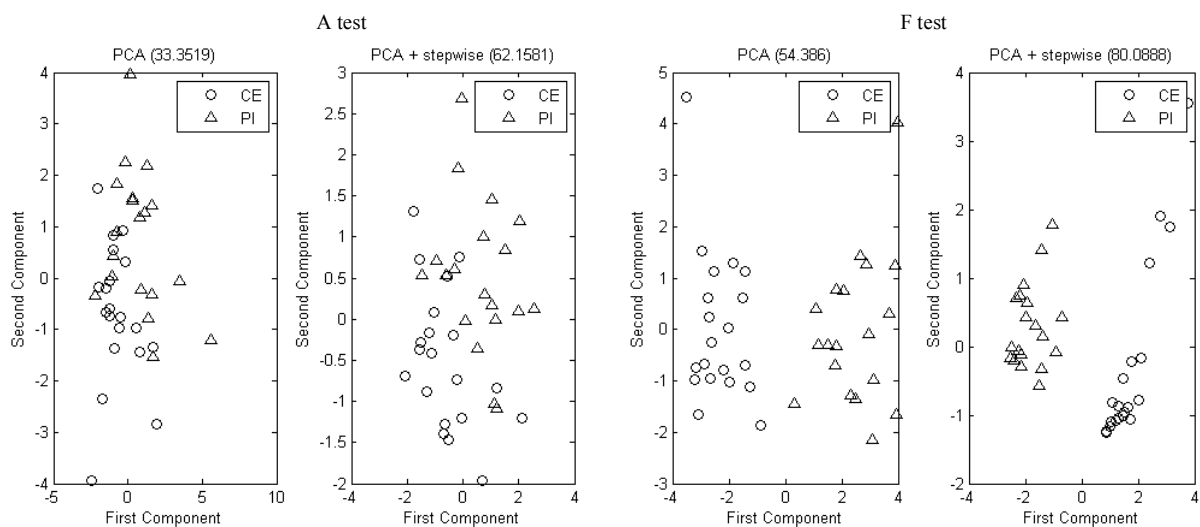


Figure 1. Loading PCA plot obtained in A and F tests using first all qualitative parameters and then those selected by the stepwise regression. Circle: Terzi's Method subjects (CE); Triangle: Control Group (PI).

After comparing the two schools for each qualitative parameter, principal component analysis (PCA) has been carried out, considering first all qualitative parameters and then only a part of them, selected by stepwise regression. Loading PCA plot (Figure 1) shows the weights for variables calculated for both groups and in relation to the first two PCA components.

Principal Component Analysis (PCA) in A test, conducted using first all parameters for each qualitative criterion and then only those selected by stepwise regression (*inefficient posture* and *handgrip, irregular word spacing, wrong graphomotor pattern*), shows that the first two components have an associated explained variance of 33.3% in the first case and 62.2% in the second case. PCA for F test, computed on all parameters and on selected parameters through stepwise regression (*letter collisions, fluctuations on the line, maximum variation of letter size, wrong letter size, wrong graphomotor pattern, self-corrections*), shows an explained variance of the first two PCA components of 54.4% and 80%. For both A and F test, using PCA on selected parameters, groups are more distinguishable.

4. Conclusion

Results confirm the hypothesis of a better qualitative performance from pupils who use the Terzi's method. Comparing the two tests, the experimental group maintains almost the same quality; unlike the control group has a slightly greater number of errors switching from accurate modality to the fast one. In the evolutionary development of the calligraphy, CE students have achieved a balance between accuracy and speed performances. PI students, from a kinematic point of view, spend more time with pen off the paper to organize the correct graphomotor pattern. In addition, PI students have a less fluent handwriting. PI student make a pen lift every letter, registering a greater number of components.

Since early years of school, Terzi's method makes a more readable and accurate writing and this result could surely support prevention from dysgraphia, although at the expense of movement fluency. The automation of accurate movements is facilitated paying special attention to improve handgrip of the writing tools used.

In the other hand, the tools deployed for the kinematic and qualitative analysis of handwriting are a good way to quantitatively evaluate graphomotor performance and can be also used in teaching methods evaluation.

References

- Losse, A., Henderson, S.E., Elliman, D., Hall, D., Knight, E. & Jongmans, M. (1991). Clumsiness in children: Do they grow out of it? A 10 year follow-up study. *DMCN*, 33, 55-68.
- Skinner, R. & Piek, J. (2001). Psychosocial implications of poor motor control coordination in children and adolescents. *Human Movement Science*, 20, 73-94.
- Cummins, A., Piek, J. & Dyck, M. (2005). Motor coordination, empathy and social behaviour in school aged children. *Developmental Medicine & Child Neurology*, 47, 437-442.
- Sülzenbrück, S., Hegele, M., Rinkenauer, G., & Heuer, H. (2011). The death of handwriting: Secondary effects of frequent computer use on basic motor skills. *Journal of motor behavior*, 43(3), 247-251.
- Hanover Research. (2012). *The Importance of Teaching Handwriting in the 21st Century*. Retrieved from <https://www.hw21summit.com>
- Martins, M.R., Bastos, J.A., Cecato, A.T., Araujo, Mde L., Magro, R.R., & Alaminos, V. (2013). Screening for motor dysgraphia in public schools. *Jornal de Pediatria (Versao em Portugues)*, 89(1), 70-74.
- Accardo, A., Genna, M., Perrone, I., Ceschia, P., Mandarino, C. (2014). Evaluation of different handwriting teaching methods by kinematic analysis. *XIII MEDICON 2013. IFMBE Proceedings*, 41, 579-582.
- Genna, M., D'Antrassi, P., Ajčević, M., Accardo, A. (2015). A New Approach for Objective Evaluation of Writing Quality. *16th Nordic-Baltic Conference on Biomedical Engineering. Springer International Publishing*, pp.32-35.
- Terzi, I. (1995). *Il Metodo spazio-temporale, basi teoriche e guida agli esercizi*. Ghedini (Eds.), Milano.
- Van Galen, G.P., Weber, J.F. (1998). On-line size control in handwriting demonstrates the continuous nature of motor programs. *Acta Psychol (Amst)*, 100, 195-216
- Genna, M., Accardo, A., Borean, M. (2011). Kinematic Analysis of Handwriting in Pupils of Primary and Secondary School, *15th IGS 2011 Conference Proc., Cancún, México*. Elena Grassi & Jose L. Contreras-Vidal (Eds.), pp.193-196.
- Djioua, M., Plamondon, R. (2009). A new algorithm and system for the characterization of handwriting strokes with delta-lognormal parameters, *IEEE Trans Pattern Anal Mach Intell*, 31(11), 2060-2072.
- Rosenblum, S., Chevion, D., Weiss, P.L. (2006). Using data visualization and signal processing to characterize the handwriting process. *Pediatric Rehabilitation*, 4, 404-17

Exploring the Kinematic Dimensions of Kindergarten Children's Scribbles

Celine REMI^a, Jean VAILLANT^a, Rejean PLAMONDON^b Lionel PREVOST^a and Theresa DUVAL^a

^aLAMIA, Département de mathématiques et informatique, Université des Antilles et de la Guyane
Campus de Fouillole, BP 250, 97 159 Pointe à Pitre Cedex Guadeloupe

^bLaboratoire Scribens, Département de Génie Électrique, École Polytechnique de Montréal
C.P. 6079 Succ. Centre-ville, Montréal, Canada, H3C 3A7

cremi@univ-ag.fr, jvaillan@univ-ag.fr, rejean.plamondon@polymtl.ca, lionel.prevost@univ-ag.fr

Abstract. This paper deals with the study of the kinematic dimension of scribbling activities executed by kindergarten children aged from 3 to 6 years old from three grades. For this purpose, three sigma-lognormal features, six classical ones and one hybrid feature related to visuo-motor skills are extracted from scribbles realized using five different Type Grib. The statistical analysis of these data illustrates that sigma-lognormal modeling can satisfactorily reconstruct kindergarten children's scribbles. Moreover, this preliminary study confirms that there are significant differences between grades with respect to six of the features we studied, regardless of the nature of the scribbling movement made by children. These features are related to rapidity, fluidity and precision of linear and curvilinear movements used for scribbling tasks.

1. Introduction

Scribbling is a spontaneous graphical ability manifested by children in early childhood. According to Lurcat (1988), children acquire this pre-writing ability when they are about 18 months old. Families do not systematically encourage this first manifestation of interest for graphical expression on all accessible surfaces. It is also not systematically given attention in kindergarten, where programming must focus on preparing children to learn handwriting.

In French and Kriol respectively, words like *gribouillage* and *makakri*, used to refer to children's scribbles, have an inherent negative connotation. Moreover, they reveal adults' judgments regarding scribbles, which are essentially related to the esthetics and meaning of the trace which is produced on the surface chosen by the young scribbler. The motor dimension of scribbling is neglected.

However, we hypothesize that scribbling process can provide relevant and useful information on the development of young children's early abilities to control their graphical movements and on the progress of their hand-eye coordination skills. For a first verification of this hypothesis, we carried out a four-month longitudinal experiment in a kindergarten school, entitled "*Y a t'il un copilote à bord ?*" ("Is there a co-pilot on board?").

This paper studies the kinematic dimension of various categories of scribbling movements which were recorded during the study. Its purpose is to determine if such dimensions can help distinguish between the levels of movement control achieved by kindergarten children according to their grade, regardless of the Type Grib. In section 2, we provide information on the participants, the tasks and the experimental conditions. In section 3, we details the feature extraction process. In section 4, the preliminary results of the statistical analysis of six classical kinematic features and four sigma-lognormal features are discussed. These results are related to 2 questions: Can sigma-lognormal modeling satisfactorily reconstruct children's scribbles? Do the values taken by some classical or sigma-lognormal features depend on kindergarten grade, or do they depend on the scribbling strategies?

2. Participants, tasks and conditions of realization

Sixty children took part in this experiment, from three kindergarten grades called '*Petite Section*' (PS), '*Moyenne Section*' (MS) and '*Grande Section*' (GS). Table 1 shows their distribution by gender and grade. PS pupils were 3-4 years old. They had 6 months of graphomotor preparation lessons (during classroom), while MS ones were 4-5 years old with 18 months of preparation. GS pupils were 5-6 years old with 30 months of preparation lessons.

Table 1. Distribution of participants according to gender (F, M) and grade (PS, MS, GS).

	GS	MS	PS	Total
F	12 (20%)	9 (15%)	8 (13%)	29 (48%)
M	17 (28%)	4 (7%)	10 (17%)	31 (52%)
Total	29 (48%)	13 (22%)	18 (30%)	60 (100%)

Each child was brought from their classroom to the experiment room by the accompanying experimenter. The child was asked to execute five scribbles according various Type Grib: S1, S2, S3, S4 and S5. The first one was spontaneous (S1) without any constraint on the type of movement. The second scribble (S2) was to produce only linear strokes all over the sheet of paper. The third (S3) was the same as S2, but the pupil was asked to draw as fast as he could. Next, for the S4 and S5 tasks, the children were asked to use only curved movements to draw their scribbles all over the sheet of paper and S5 had to be realized faster than S4.

For each of these productions, the pupil was asked to begin their scribble when they heard a randomized audio signal. They were asked to produce 20 seconds of scribbling trying to keep the pen down for the entire period. During the online acquisition of the child's scribbling movements, the experimenter took a seat in front of a computer and the child sat in front of a digitizing tablet according to the configuration shown in Figure 1. The experimenter verified that the child was correctly seated and that they felt comfortable writing on the tablet.



Figure 1. Workstation used at the kindergarten for the experiment session

To ensure that the task had been properly understood, the experimenter showed the requested movement with his fingertip systematically before each child had to execute a new Type Grib. The numbers of scribbles, which were recorded for each condition, are provided in Table 2.

Table 2. Numbers of scribbles recorded by grade and gender for each condition: S1, S2, S3, S4 and S5.

Type Grib	GS		MS		PS		All grades
	F	M	F	M	F	M	
S1	12	16	9	4	8	10	59
S2	11	15	6	3	6	9	50
S3	11	17	9	3	7	9	56
S4	12	17	8	4	7	10	58
S5	11	17	8	4	8	9	57
All types	57	82	40	18	36	47	280

3. Feature extraction from scribbles

In the present study, we focus on two sets of features that can be called the classical dynamic set and the sigma-lognormal set. The extraction process is illustrated in Figure 2. First, for each scribble, the raw data are digitized by the *Wacom Intuos* tablet with a sampling rate of 200 Hz. The pressure $p(t)$ and the two-dimensional position $(x(t), y(t))$ of the pen tip are recorded using *DekatTras* software for 10 seconds from the fifth second of scribbling. Next, on the basis of these raw data, six classical features are computed.

Figure 2 provides also the names of the classical features in bold fonts and those of the sigma-lognormal in Italics. The six classical features correspond respectively to (1) the length of the trajectory of the pen tip on the surface of the tablet, (2) the surface scribbled by the child, (3) the value of the pen-up duration, (4) the number of velocity peaks, (5, 6) the values of the maximal and minimal pressure on the pen tip. These features have already shown their usefulness in characterizing the degree of visuo-motor maturation (Rosemblum et al. 2003, Chartrel and Vinter 2010).

Then, the preprocessing software is used to convert the raw date file into HWS format. The *ScriptStudio* software uses these inputs to estimate three sigma-lognormal features. As illustrated in Figure 3, *ScriptStudio* conducts sigma-lognormal modeling which describes the velocity of planar movements (e.g. handwritten trajectories) as a vector summation of neuromuscular components that have a weighted and time-shifted lognormal velocity profile and a circle-arc trajectory. The mathematical definition of this model has been described and explained numerous times. Interested readers can refer to the relevant technical publications for mathematical details (Plamondon and Djioua 2006, O'Reilly and Plamondon 2009).

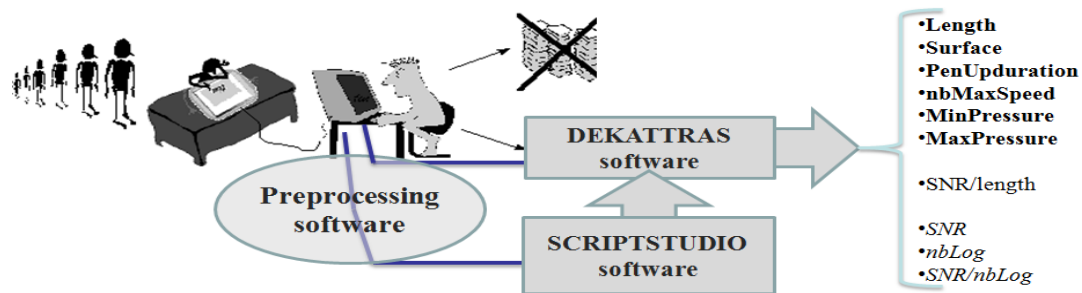


Figure 2. Feature extraction process. Bold type indicates classical features, Italic font indicates sigma-lognormal features and Roman type indicates hybrid feature.

Our analyses used features extracted from this segmentation process: the signal-to-noise ratio of the reconstruction process (O'Reilly and Plamondon 2009), the number of basic lognormal strokes used for modeling (*nbLog*), and the ratio of these two variables (*SNR/nbLog*). This last variable reflects the writer's ability to make regular movements. It is a good global indicator of the graphomotor performance of a given writer. Altogether, these variables are considered to index the lognormality of the produced movements, a concept similar to movement smoothness (Plamondon et al 2013).

Lastly, we have introduced a new feature which is built from a classical one and a sigma-lognormal one. It is the SNR ratio divided by the length of the trajectory produced by the inking pen tip on the sheet of paper.

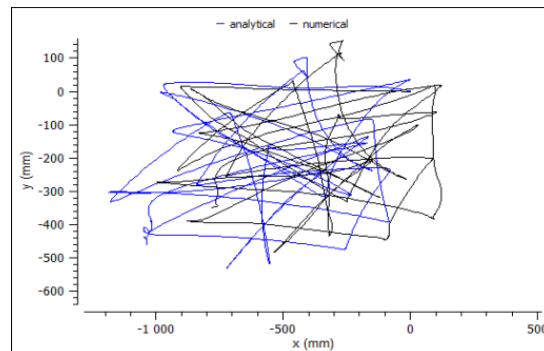


Figure 3. Example of a child' scribble (in blue) and its Sigma-Lognormal reconstruction (in black).

4. Statistical analysis of the features

ANOVA tests, Kruskal-Wallis tests and PCA analyses were carried out on the dataset consisting of 10 features in order to respond to the questions considered in the introduction section. Results are presented in the followings.

4.1 Reconstructing children' scribbles using Sigma-lognormal modeling

To answer the first question (Can sigma-lognormal modeling satisfactorily reconstruct children's scribbles?), we calculated the SNR histogram for all the scribbles (Figure 4). This distribution corresponds to SNR values before correction of the speed values at the beginning and the end of the truncated 10-second signal. 85% of the scribbles have an SNR greater than 15db and 58% of them have an SNR greater than 18db. The 15dB value has often been judged as sufficient to analyze elderly adults with declining handwriting (Plamondon et al. 2013, Woch et al 2011) and young children's productions of pattern movements (Duval et al. 2013). On this basis, we used the same threshold here to produce our statistical study of the behaviours of the sigma-lognormal features in conjunction with the classical ones.

4.2 Grade and on Type Grib impact features

The non-parametric and parametric statistical tests used to study the effects of the two factors, Grade and Type Grib, with respect to the 10 classical and sigma-lognormal features, reveal a significant effect for most of those features. Besides, systematically, when an effect of Type Grib is significant, grade has a significant effect too.

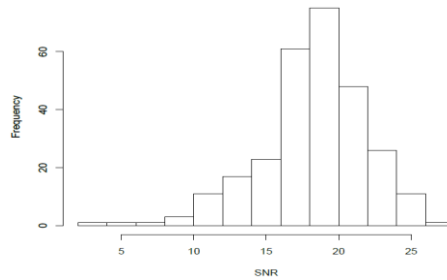


Figure 4. SNR distribution.

Table 3. Significance of features (x = significant effect, NS = non-significant effect)

Test	Factor	SNR	NbLog	SNR/Length	surface	SNR/NbLog	Length	nbPenUp	nbMaxSpeed	minPressure	maxPressure
ANOVA	Grade	x	x	x	x	x	x	x	NS	NS	NS
Kruskal-Wallis	Grade	x	x	x	NS	x	x	x	x	x	x
ANOVA	Type Grib	x	x	x	NS	x	x	x	NS	NS	NS
Kruskal-Wallis	Type Grib	x	x	x	NS	x	x	x	x	NS	x
		4/4	4/4	4/4	1/4	4/4	4/4	4/4	2/4	1/4	1/4

5. Conclusion and perspectives

In this paper, we first showed that sigma-lognormal modeling can provide satisfactory reconstructions of scribbles produced by young children in kindergarten. This observation constitutes a preliminary result that may help us design studies of the kinematic stability of various Type Grib taking into account a similar sigma-lognormal approach (Pirlo et al. 2013). Moreover, for six features related to fundamental dynamic abilities such as rapidity, fluidity and precision of fine movements, our analysis shows that there are significant differences between grades and that there are also significant differences from one scribbling strategy to the next. Future research includes analysis of how gender impacts all these abilities.

Scribbling ability is not yet used in kindergarten as an objective way to assess children's graphomotor skills for teaching purposes. The preliminary results of our study "Y a t'il un copilote à bord?" may inspire further studies about the potential relevance of graphomotor training for very young children. One of the main points of interest relative to graphomotor training tasks is that it is not necessary for a child to have a well-developed socio-linguistic background to be able to scribble. Moreover, it is a familiar activity that can be carried out by children starting in the first grade of kindergarten regardless of the child's language and linguistic background.

With this in mind, we launched a three-year longitudinal experiment in January 2015 in an experimental preschool structure called "Lakou TiFilawo: le bon Départ" ("the good start").

References

- Lurçat, Liliane. (1971, éd. 1988). *L'activité graphique à l'école maternelle* (4ème éd.). France, Paris: ESF editions.
- Rosenblum S., Parush, S., Weiss, P.L. (2003). "Computerized Temporal Handwriting Characteristics of Proficient and Non-proficient Hand-Writers." *The American Journal of Occupational Therapy*, 57 (2), 129-138.
- Chartrel, E. and Vinter, A. (2010). "Effects of different types of learning on handwriting movements in young children." *Learning and Instruction* (20), 476-486.
- Plamondon, R. and Djoua, M. (2006) "A multi-level representation paradigm for handwriting stroke generation." *Human Movement Science*, 25 (4-5), 586-607.
- O'Reilly, C. and Plamondon, R. (2009). "Development of a sigma-lognormal representation for online signatures." *Pattern Recognition*, 42 (12), 3324-3337.
- Plamondon, R., O'Reilly, C., Rémi, C. and Duval, T. (2013). "The lognormal handwriter: learning, performing and declining." *Frontiers in Psychology*, 945 (4), 1-14. doi: =10.3389/fpsyg.2013.00945 www.frontiersin.org/Cognitive_Science/10.3389/fpsyg.2013.00945/full
- Woch, A., Plamondon, R. and O'Reilly, C. "Kinematic characteristics of bidirectional delta-lognormal primitives in young and older subjects." *Human Movement Science* 30 (1): 1-17, 2011.
- Duval, T., Rémi, C., Plamondon, R. and O'Reilly, C. "On the use of the sigma-lognormal model to study children's handwriting." *16th Biennial Conference of the International Graphonomics Society*. Nara, Japan, June 2013 (p. 26-29)
- Pirlo, G., Impedovo, D., Plamondon, R., O'Reilly, C., Cozzolongo, A., Gravinese, R. and Rollo, A. (2013). "Stability of dynamic signatures: from the representation to the generation domain." *17th International Conference on Image Analysis and Processing, ICIAP 2013*, v. 8158 LNCS, p. 122-130

A Dissimilarity Measure for On-Line Signature Verification Based on the Sigma-Lognormal Model

Andreas Fischer*^{†‡} and Réjean Plamondon*

*Laboratoire Scribens, École Polytechnique de Montréal, Canada, {andreas.fischer,rejean.plamondon}@polymtl.ca

[†]DIUF Department, University of Fribourg, Switzerland, andreas.fischer@unifr.ch

[‡]iCoSys Institute, University of Applied Sciences and Arts Western Switzerland, andreas.fischer@hefr.ch

Abstract—The Sigma-Lognormal model of the Kinematic Theory of rapid human movements allows us to represent on-line signatures with an analytical neuromuscular model. It has been successfully used in the past to generate synthetic signatures in order to improve the performance of an automatic verification system. In this paper, we attempt for the first time to build a verification system based on the model parameters themselves. For describing individual lognormal strokes, we propose eighteen features which capture cognitive psychomotor characteristics of the signer. They are matched by means of dynamic time warping to derive a dissimilarity measure for signature verification. Promising initial results are reported for an experimental evaluation on the SUSIG visual sub-corpus, which contains some of the most skilled forgeries currently available for research.

Keywords—on-line signature verification; Kinematic Theory of rapid human movements; Sigma-Lognormal model

I. INTRODUCTION

Signatures are widely used biometrics for personal authentication. In contrast to *off-line* images of signatures, modern digitizers such as tablet computers and smartphones capture *on-line* signatures, that is the trajectory of the pen tip over time possibly enriched with additional information such as the pressure of the pen [1]. The time dimension allows an analysis of movement patterns in addition to static images, which usually leads to a much higher performance for automatic signature verification [2].

Many models have been proposed to analyze human movement patterns in general and handwriting in particular, including coupled oscillator models [3], minimum jerk models [4], and models relying on neural networks [5] to name just a few.

Among them, the Kinematic Theory of rapid human movements is a unique framework based on the lognormal law [6], [7]. It includes a family of analytical models for representing movements based on neuromuscular strokes with lognormal velocity [8]. The Delta-Lognormal model represents single rapid movements by means of two strokes in opposite direction. Similarly, the Omega-Lognormal model represents oscillatory movements with an alternating sequence of opposed strokes. Finally, the Sigma-Lognormal model has been proposed to represent complex movements like signatures using a vectorial sum of lognormal strokes [9].

Robust algorithms have been developed for estimating the lognormal parameters from observed trajectories [10], [11]. They achieve an excellent reconstruction quality of the observed movement provided that the movement is skilled and unimpaired. On the other hand, it has been shown recently that

aging, for example, leads to a deviation from lognormality in handwriting movements when the control of the fine motricity begins to decline and on the other hand, as children improve in learning handwriting, their movements tend toward lognormality [12].

Apart from its powerful potential in biomedical and neuroscience applications, one of the most successful applications of the Kinematic Theory has been the synthetic generation of handwriting based on the analytical model, for example gestures [13], signatures [14], [15], and also unconstrained handwriting [16]. The synthetic specimens could be used as learning samples to improve an automatic recognition system. This is particularly interesting for signature verification, where only few reference signatures are available per user.

In this paper, we go a step further and aim to build a signature verification system based on cognitive psychomotor characteristics captured by the model itself. Such characteristics have been linked recently with brain stroke risk factors [17], which highlights the promising potential of the model in the context of biometric verification. We propose a new dissimilarity measure between two signatures based on their Sigma-Lognormal representation. Eighteen features are suggested for describing an individual stroke and the stroke sequences are matched by means of dynamic time warping. Initial results are reported for the highly skilled forgeries of the SUSIG visual sub-corpus [18].

The remainder of this paper is organized as follows. The data set and the model parameter extraction are discussed in Section II. Afterwards in Section III, the proposed dissimilarity measure for signature verification is introduced. Finally, experimental results are reported in Section IV and conclusions are drawn in Section V.

II. MODEL EXTRACTION

A. Data Set

On-line signatures from the SUSIG visual sub-corpus [18] are considered in this paper. It includes signatures from 94 users captured with Interlink Electronics's ePad-ink tablet. This tablet has a pressure-sensitive LCD screen which shows the signer what he or she is writing.

For every user, highly skilled forgeries were created based on animations of the signature to imitate. The animations were shown on the LCD screen so that the forger could trace over the genuine signature in several attempts. This acquisition protocol has allowed to generate some of the most skilled forgeries currently available for research.

B. Sigma-Lognormal Model

The Sigma-Lognormal model ($\Sigma\Lambda$) [9] represents on-line signatures $s = (s_1, \dots, s_N)$ as a sequence of strokes. Each stroke s_i has lognormal speed

$$|\vec{v}_i(t)| = \frac{D_i}{\sqrt{2\pi}\sigma_i(t-t_{0_i})} \exp\left(-\frac{(\ln(t-t_{0_i})-\mu_i)^2}{2\sigma_i^2}\right) \quad (1)$$

with respect to the initialization time t_{0_i} , the input command D_i which corresponds with the covered distance when executed in isolation, and the two parameters μ_i and σ_i related to the logtime delay and the logresponse time of the neuromuscular system responding to the command.

The angular position of the movement along a pivot direction is expressed with respect to the start angle θ_{s_i} and the end angle θ_{e_i} . In total, each stroke is represented by six parameters

$$s_i = (D_i, t_{0_i}, \mu_i, \sigma_i, \theta_{s_i}, \theta_{e_i}) \quad (2)$$

which allow a reconstruction of the observed velocity by means of vectorial summation:

$$\vec{v}_r(t) = \sum_{i=1}^n \vec{v}_i(t) \quad (3)$$

The quality of the reconstruction is measured as a signal-to-noise ratio taking into account the observed velocity $\vec{v}_o(t)$ and the reconstructed velocity $\vec{v}_r(t)$

$$SNR = 10 \log \left(\frac{\int_{t_s}^{t_e} |\vec{v}_o(\tau)|^2 d\tau}{\int_{t_s}^{t_e} |\vec{v}_o(\tau) - \vec{v}_r(\tau)|^2 d\tau} \right) \quad (4)$$

where t_s is the start time and t_e is the end time of the pen tip trajectory.

C. Parameter Extraction

Recently, a robust algorithm for the extraction of the Sigma-Lognormal model from the observed pen tip trajectory has been introduced in [11]. It iteratively adds lognormal strokes to the model in order to maximize the SNR.

Each pen-down component is analyzed separately as suggested in [16]. The pen tip is stopped artificially at the beginning and at the end of each component to ensure zero velocity for an improved extraction of the first and the last stroke. Furthermore, signal preprocessing includes an interpolation with cubic splines, resampling at 200Hz, and low pass filtering with a Chebyshev filter to remove high-frequency components introduced by the digitizer.

Afterwards, one stroke after the other is extracted from the preprocessed observed velocity $\vec{v}_o(t)$ in three steps. First, s_i is localized in the speed profile $|\vec{v}_o(t)|$ based on local minima and maxima. Secondly, the stroke parameters $s_i = (D_i, t_{0_i}, \mu_i, \sigma_i, \theta_{s_i}, \theta_{e_i})$ are estimated based on the analytical Robust XZERO solution [11] as well as non-linear least squares curve fitting. Thirdly, s_i is added to the result and $\vec{v}_i(t)$ is subtracted from $\vec{v}_o(t)$. The three steps are repeated until the SNR cannot be further improved.

A reconstruction example is illustrated in Figure 1. Individual strokes are shown in the trace as well as in the velocity profile. Virtual target points are marked with a circle. They

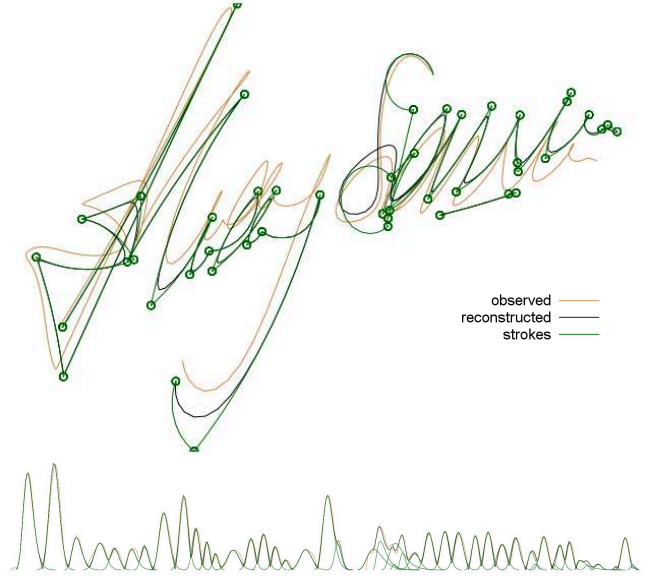


Fig. 1. Reconstructed trace and velocity profile of an on-line signature.

would have been reached if the strokes were executed in isolation rather than computing the vectorial sum in Equation 3. The reconstructed velocity profile is very accurate with an average SNR of 18.5dB for the three pen-down components.

III. SIGNATURE VERIFICATION

For automatic signature verification, we represent the questioned signature $q = (q_1, \dots, q_N)$ and the reference signatures $r = (r_1, \dots, r_M) \in R$ with a sequence of strokes based on the Sigma-Lognormal model. Then, we compute a dissimilarity $\hat{d}_R(q)$ between the questioned signature q and the set of reference signatures R , which is compared with a threshold in order to accept or reject the questioned signature.

In the following, features for describing an individual stroke are presented in Section III-A and the dissimilarity measure $\hat{d}_R(q)$ is derived in Section III-B based on dynamic time warping.

A. Stroke Features

Eighteen features are proposed to characterize a stroke $s_i = (D_i, t_{0_i}, \mu_i, \sigma_i, \theta_{s_i}, \theta_{e_i})$. The first seven features correspond directly with model parameters

- $f_1 = D_i$
- $f_2 = \mu_i$
- $f_3 = \sigma_i$
- $f_4 = \sin(\theta_{s_i})$
- $f_5 = \cos(\theta_{s_i})$
- $f_6 = \sin(\theta_{e_i})$
- $f_7 = \cos(\theta_{e_i})$

considering Cartesian coordinates $(\sin(\alpha), \cos(\alpha))$ for angular parameters. For the initialization time t_{0_i} , we compute a feature in comparison with the preceding stroke s_{i-1}

- $f_8 = \Delta t_0 = t_{0_i} - t_{0_{i-1}}$

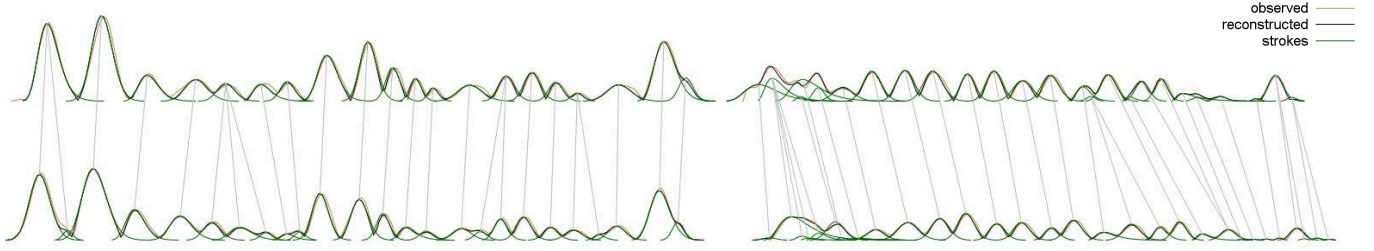


Fig. 3. Stroke alignment using dynamic time warping.

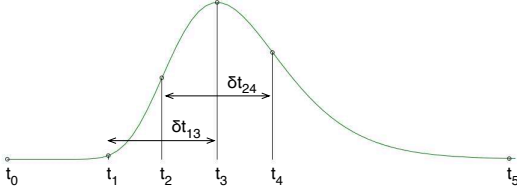


Fig. 2. Characteristic times of a lognormal stroke.

The remaining features are calculated with respect to five characteristic times t_{1_i}, \dots, t_{5_i} of a lognormal stroke [11]. They are illustrated in the velocity profile in Figure 2. The times t_{2_i}, t_{3_i} , and t_{4_i} are the zeroes of the first and second derivative of the lognormal Equation 1 and correspond respectively to the mode $t_{3_i} = t_{0_i} + \exp(\mu_i - \sigma_i^2)$ and the inflection points of the lognormal stroke. The other times $t_{1_i} = t_{0_i} + \exp(\mu_i - 3\sigma_i)$ and $t_{5_i} = t_{0_i} + \exp(\mu_i + 3\sigma_i)$ are chosen such that the interval $[t_{1_i}, t_{5_i}]$ contains 99.97% of the area under the lognormal curve. Based on these characteristic times, the remaining ten features are defined as

- $f_9 = v_2 = |\vec{v}_i(t_{2_i})|$
- $f_{10} = v_3 = |\vec{v}_i(t_{3_i})|$
- $f_{11} = v_4 = |\vec{v}_i(t_{4_i})|$
- $f_{12} = \delta t_{05} = t_{5_i} - t_{0_i}$
- $f_{13} = \delta t_{15} = t_{5_i} - t_{1_i}$
- $f_{14} = \delta t_{13} = t_{3_i} - t_{1_i}$
- $f_{15} = \delta t_{35} = t_{5_i} - t_{3_i}$
- $f_{16} = \delta t_{24} = t_{4_i} - t_{2_i}$
- $f_{17} = \Delta t_1 = t_{1_i} - t_{1_{i-1}}$
- $f_{18} = \Delta t_3 = t_{3_i} - t_{3_{i-1}}$

They capture detailed timing characteristics of the neuromuscular Sigma-Lognormal model.

B. Dissimilarity Measure

In order to compute a distance $d(q, r)$ between the questioned signature $q = (q_1, \dots, q_N)$ and a reference signature $r = (r_1, \dots, r_M) \in R$ with a different number of strokes, we consider the dynamic time warping distance (DTW) [19]

$$d(q, r) = \min_p \sum_{i=1}^{|p|} |f_k(q_{p_{i,1}}) - f_k(r_{p_{i,2}})| \quad (5)$$

with respect to one of the features f_k , $k \in 1, \dots, 18$, and the time warping path p , which is illustrated in Figure 3.

Based on the DTW distance $d(q, r)$, the minimum distance

$$d_R(q) = \min_{r \in R} d(q, r) \quad (6)$$

to the set of reference signatures R is computed. Finally, this value is normalized

$$\hat{d}_R(q) = \frac{d_R(q)}{\mu_d} \quad (7)$$

with the mean score $\mu_d = \frac{1}{|R|} \sum_{i=1}^{|R|} d_{R \setminus r_i}(r_i)$ computed over all reference signatures to make it comparable across different users in the database.

IV. EXPERIMENTAL EVALUATION

In this section, we present the results of a preliminary evaluation of the proposed method for skilled forgery detection on the SUSIG visual sub-corpus (see Section II-A).

A. Setup

All available genuine signatures and skilled forgeries are used in the trial. For each of the 94 users, the first 5 signatures are used as references and the remaining 15 for evaluation. In total, we consider $94 \cdot 5 = 470$ reference signatures, $94 \cdot 15 = 1,410$ genuine signatures, and $94 \cdot 10 = 940$ skilled forgeries.

The performance is evaluated in terms of equal error rate (EER), that is the point in the receiver operating characteristic (ROC) where the false acceptance rate equals the false rejection rate.

B. Model Quality

The extraction algorithm (see Section II-C) for the Sigma-Lognormal model achieves an SNR of 19.87 ± 2.40 dB for the SUSIG visual sub-corpus. This is a good reconstruction quality when compared with 15dB which is generally considered as sufficient for human movement analysis [10]. 96.77% of all signatures were reconstructed with an SNR above this threshold.

C. Verification Results

Table I lists the EER results for the best seven out of eighteen investigated features. The main observation is that the best performing features on this data set are those related to timing differences, both within the same stroke and between two consecutive strokes. The overall best performance is achieved with the feature Δt_3 , that is the difference between the mode of two consecutive strokes.

Rank	Feature	EER
1.	Δt_3	5.11%
2.	Δt_1	5.43%
3.	δt_{24}	8.94%
4.	δt_{13}	8.94%
5.	δt_{05}	13.83%
6.	δt_{15}	14.47%
7.	Δt_0	15.11%

TABLE I. EER RESULTS FOR THE SUSIG VISUAL SUB-CORPUS.

Furthermore, it is interesting to notice that features with respect to the four characteristic times t_1 , t_2 , t_3 , and t_4 lead to a significantly better performance than features related to the initialization time t_0 and the end time t_5 . These two parameters are particularly difficult to estimate with our current model extraction algorithm when several strokes overlap in time [20].

When compared with the state of the art, the EER of 5.11% obtained with the proposed method is in the ballpark of the best results reported for this difficult verification task. In [21], Sae-Bae and Memon report an EER of 6.08% with a recent histogram-based system. By fine-tuning the system to the data set, an EER of 4.37% is achieved. In [22], Yanikoglu and Kholmatov propose a verification based on Fourier descriptors and report an EER of 6.20%. When combined with a second DTW-based verification system, an EER of 3.03% is obtained.

V. CONCLUSIONS

In this paper, we have introduced one of the first pattern recognition systems which is directly based on the Sigma-Lognormal model. Instead of using the model to generate synthetic movements, cognitive psychomotor characteristics of the signer are derived from the model itself and are integrated into a signature verification system.

A preliminary evaluation on the SUSIG visual sub-corpus has demonstrated that the proposed method is able to achieve state-of-the-art results for skilled forgery detection. Difficult forgeries are taken into account that were created by tracing animated genuine signatures on an LCD screen.

In order to build a complete system that includes the proposed Sigma-Lognormal verifier, future work includes a more comprehensive experimental evaluation, the combination of complementary features, and also the combination of complementary verification systems. The Sigma-Lognormal verifier is expected to have a particular advantage for detecting highly skilled forgeries when compared with other approaches. Even if the trace signals and the velocity signals are very similar, the model might be able to distinguish nuanced differences in the fine motor control.

ACKNOWLEDGMENTS

This work has been supported by the Swiss SNSF grant P300P2-151279 to A. Fischer and the Canadian NSERC grant RGPIN-915 to R. Plamondon.

REFERENCES

[1] R. Plamondon and S. N. Srihari, "Online and off-line handwriting recognition: A comprehensive survey," *IEEE Trans. PAMI*, vol. 22, no. 1, pp. 63–84, 2000.

[2] D. Impedovo and G. Pirlo, "Automatic signature verification: The state of the art," *IEEE Trans. on Systems, Man, and Cybernetics, Part C: Applications and Reviews*, vol. 38, no. 5, pp. 609–635, 2008.

[3] J. Hollerbach, "An oscillation theory of handwriting," *Biological Cybernetics*, vol. 39, no. 2, pp. 139–156, 1981.

[4] T. Flash and N. Hogans, "The coordination of arm movements: An experimentally confirmed mathematical model," *Journal of Neuroscience*, vol. 5, pp. 1688–1703, 1985.

[5] G. Gangadhar, D. Joseph, and V. Chakravarthy, "An oscillatory neuromotor model of handwriting generation," *Int. Journal on Document Analysis and Recognition*, vol. 10, no. 2, pp. 69–84, 2007.

[6] R. Plamondon, "A kinematic theory of rapid human movements. I. movement representation and generation," *Biological Cybernetics*, vol. 72, no. 4, pp. 295–307, 1995.

[7] —, "A kinematic theory of rapid human movements. II. movement time and control," *Biological Cybernetics*, vol. 72, no. 4, pp. 309–320, 1995.

[8] R. Plamondon and M. Djioua, "A multi-level representation paradigm for handwriting stroke generation," *Human Movement Science*, vol. 25, no. 4–5, pp. 586–607, 2006.

[9] R. Plamondon and W. Guerfali, "The generation of handwriting with delta-lognormal synergies," *Biological Cybernetics*, vol. 78, pp. 119–132, 1998.

[10] M. Djioua and R. Plamondon, "A new algorithm and system for the characterization of handwriting strokes with Delta-Lognormal parameters," *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 31, no. 11, pp. 2060–2072, 2009.

[11] C. O'Reilly and R. Plamondon, "Development of a sigma-lognormal representation for on-line signatures," *Pattern Recognition*, vol. 42, no. 12, pp. 3324–3337, 2009.

[12] R. Plamondon, C. O'Reilly, C. Rémi, and T. Duval, "The lognormal handwriter: learning, performing, and declining," *Frontiers in Psychology*, vol. 4, no. 945, 2013.

[13] A. Almaksour, E. Anquetil, R. Plamondon, and C. O'Reilly, "Synthetic handwritten gesture generation using sigma-lognormal model for evolving handwriting classifier," in *Proc. 15th Int. Conf. of the International Graphonomics Society*, 2011, pp. 98–101.

[14] J. Galbally, R. Plamondon, J. Fierrez, and J. Ortega-Garcia, "Synthetic on-line signature generation. Part I: Methodology and algorithms," *Pattern Recognition*, vol. 45, no. 7, pp. 2610–2621, 2012.

[15] —, "Synthetic on-line signature generation. Part II: Experimental validation," *Pattern Recognition*, vol. 45, no. 7, pp. 2622–2632, 2012.

[16] A. Fischer, R. Plamondon, C. O'Reilly, and Y. Savaria, "Neuromuscular representation and synthetic generation of handwritten whiteboard notes," in *Proc. 14th Int. Conf. on Frontiers in Handwriting Recognition*, 2014, pp. 222–227.

[17] C. O'Reilly, R. Plamondon, and L.-H. Lebrun, "Linking brain stroke risk factors to human movement features for the development of preventive tools," *Frontiers in Aging Neuroscience*, vol. 6, 2014.

[18] A. Kholmatov and B. Yanikoglu, "SUSIG: an on-line signature database, associated protocols and benchmark results," *Pattern Analysis and Applications*, vol. 12, no. 3, pp. 227–236, 2009.

[19] —, "Identity authentication using improved online signature verification method," *Pattern Recognition Letters*, vol. 26, no. 15, pp. 2400–2408, 2005.

[20] A. Woch and R. Plamondon, "Rapid movement analysis with the Delta-Lognormal model: Towards a better understanding of movement generation," in *Proc. 10th Biennial Conference of the International Graphonomics Society*, 2001, pp. 165–196.

[21] N. Sae-Bae and N. Memon, "Online signature verification on mobile devices," *IEEE Trans. on Information Forensics and Security*, vol. 9, no. 6, pp. 933–947, 2014.

[22] B. A. Yanikoglu and A. Kholmatov, "Online signature verification using Fourier descriptors," *Eurasip Journal on Advances in Signal Processing*, vol. 2009, pp. 1–14, 2009.

Hyper-spectral Analysis for Automatic Signature Extraction

Muhammad Imran MALIK^a, Sheraz AHMED^a, Faisal SHAFAIT^c, Ajmal Saeed MIAN^c,
Christian NANSEN^c, Andreas DENGEL^a, and Marcus LIWICKI^{a,b}

^a*German Research Center for Artificial Intelligence (DFKI), Kaiserslautern, Germany*

^b*Department of Informatics, University of Fribourg, Switzerland*

^c*University of Western Australia, Perth, Australia*
firstname.lastname@dfki.de

Abstract. Signatures are one of the most accessible and prevailed ways of authenticating documents. Over the last many years, a large number of signature verification systems have been reported. A common assumption in nearly all of these system is that the signatures are available readily extracted from documents. In this paper we provide a detailed literature survey on the subject and argue that pre-extracted signatures are not always available especially in forensic cases. Furthermore, we present a novel system of automatically extracting signatures from documents with the help of hyper-spectral imaging. Initial experiments reveal that the proposed idea possess great potential to form a baseline signature extraction system above whom any signature verification system can be adjuncted for signature verification.

1. Introduction

Today automatic systems facilitate us in almost every field of life. This utility varies from simple vending and ATM machines to sophisticated systems for automatically processing images and videos (Malik et al. (2013)). As the technology grew over the last few years, various systems for automatically extracting different types of information from paper document images are reported. Automatic sorting of postal mails, optical character recognition, automatic extraction of names, addresses, numbers, dates from document images, etc., are to name a few. Once extracted, each piece of information can be used for various purposes including authentication of documents.

Signatures are a widely prevailed modality used for authentication in different sectors from banking and financial institutions to forensic departments around the world. Over the last four decades a large number of offline (using only spatial information, e.g., scanned signature images) and online (using both spatial and temporal/dynamic information of signatures) signature verification systems have been reported. In almost all of these systems a common assumption is that the signatures will be always available in a form where these systems can be applied directly. Accordingly, such signature verification systems are trained (during development) and tested (during evaluation) on signatures that are already extracted from documents (usually manual extraction is performed— before or after taking the image of signatures/documents). Moreover, publicly available signature datasets also contain only pre-extracted signatures (Ahmed et al. (2012)). We, however, note that in the real world scenario, e.g., in bank checks, wills, pay slips, invoices, and contracts, etc., signatures are available along with other diverse information, such as background text, tables, stamps, and logos, etc.

Considering this, the state-of-the-art signature identification and verification systems cannot be used, as is, in realistic scenarios. In this paper we focus on the challenges which must be handled in order to develop fully automatic document analysis system capable of first extracting important information, such as signatures, from documents and then performing operations like identification and/or verification. Furthermore, we present our novel idea of automatically extracting signatures from documents with the help of hyper-spectral imaging (HSI). For our experiments, we have developed a novel HSI document dataset containing non-overlapping as well as overlapping signatures with background text, tables, stamps, and sometimes logos. The experiments prove our idea of using HSI for automatic signature extraction from documents very successful and we report the results of the same in this paper.

2. State-of-the-Art Information Extarction Systems

Extraction of signatures from document images has not been considered by many researchers. However, segmentation/separation of handwritten text from printed text using neural networks, Hidden Markov Models (HMM), Trained Fisher classifier, and Markov Random Fields have been reported (Guo and Ma (2001); Imade, Tatsuta and Wada (1993); Kuhnke, Simoncini and Kovacs-V (1995); Zheng, Li and Doermann (2004); Chanda, Franke and Pal (2010)). Specific methods for extraction of signatures from bank checks based on filiformity criteria and prior knowledge of Cartesian coordinate space have also been reported (Djeziri, Nouboud and Plamondon (1998); Madasu et al. (2003); Sankari, Benazir and Bremananth (2010)). Many documents other than bank checks also contain signatures. A public dataset, namely Tobacco-800, consisting of complex document images containing patch level information for 900

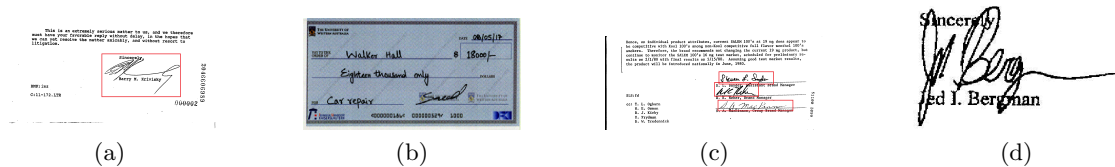


Figure 1. (a), (b), (c) Signatures at different positions in document images, (d) Signature overlapping with text

signatures along with other information is available (Zhu et al. (2007)). Zhu et al. (2007); Mandal, Roy and Pal (2011); Ahmed et al. (2012) have reported methods based on saliency map, conditional random fields, and SURF, respectively, for segmenting signatures from complete documents from subsets of Tobacco-800 dataset. These approaches segment signatures on patch level (in the form of block containing signatures and background), but fail in the cases where machine printed text touches signatures (Mandal, Roy and Pal (2011); Ahmed et al. (2012)). Some commercial systems capable of finding one or two signatures in bank checks and IRD snippets and later apply signature verification are available, e.g., SignatureXpert-2¹ by Parascript.

To the best of authors' knowledge, no method of automatic signature extraction from document images using HSI is reported in the literature. Therefore, we provide an overview of the existing automatic methods available for general hyper-spectral document image analysis. Shiel, Rehbein and Keating (2009); Aalderink et al. (2009) applied to perform quality text recovery, segmentation, and dating of historical documents from the 16th and 19th centuries based on the distribution of different types of ink and identification of corrosion. D. Goltz et al. Goltz et al. (2010) used HSI for assessing of stains, in terms of number of pixels, on the surface of historical documents. HSI is also applied for automatic forgery detection in documents based on different inks, particularly, red, blue, and black gel inks and in combination with the Fourier transform spectroscopy (Khan, Shafait and Mian (2013); Morales et al. (2014); Silva et al. (2014); Reed et al. (2014); Brauns and Dyer (2006)).

3. Hyper-spectral Imaging for Automatic Signature Extraction

We have developed a dataset containing patches from 100 document images, scanned using hyper-spectral camera with a very high spectral resolution of 2.1 nm. In addition to a high spectral resolution, this camera covers the complete visible region and infrared region (upto 900 nm). The image scanned using this hyper-spectral camera has 240 bands. The acquired data contain non overlapping, partially overlapping and completely overlapping signatures with stamps, machine printed text, tables, and logos. Bounding boxes (rectangular boxes containing signatures and overlapping objects if any within the bounds of signatures) are provided as ground truth in every case.

We propose the idea of applying part-based keypoint detection method (e.g., SURF) in conjunction with hyper-spectral imaging for automatic signature extraction from document images. As we scanned the documents using a hyper-spectral camera having 240 bands, each pixel has 240 values. Our analysis reveals that printers' inks have significant responses on almost all of the 240 band. While the pens' inks have significant response on some layers but little or no response on the others (different pens had different responses, but all of them disappeared on some layers of HSI). This can be seen in Figure 2 (a) where spectral responses of background, printed text, and signature pixel are shown. This observations serves as a building block for our methodology. Based on this observation, we first find the band where all the content of a document (including signature) has significant response, and then the band where signature has minimal or preferably no response. To find these bands we apply the SURF keypoint detector and count the total number of keypoints on each band, this enables us find the band with maximum number of keypoints (the band that contains the signature plus nearly all the background) and the band with the minimum number of keypoints (the band that contains potentially only signature). Once we get the two bands, we perform noise removal and morphological operations and finally subtract the band without signatures from the one with the signatures, thereby leaving us with the signatures.

Figure 2 (b) shows an example of what we actually get by applying our approach. This is infact the actual result we got on one of the documents. Note that the said approach is fully automatic and does not require human intervention at any step. Once signatures are extracted, any signature verification system can be applied or even a forensic expert can perform comparison experiments later on.

Our experiments on a set of 100 HSI scanned documents achieved the results given in Table 1. The following standard measures are used to report the system performance.

- Precision: the measure which represents that out of the total retrieved signature bounding boxes (an overlap of more than 50% marks a true positive), how many actually contain signatures.

¹ <http://www.parascript.com/recognition-products/forms-processing/signaturexpert-2>

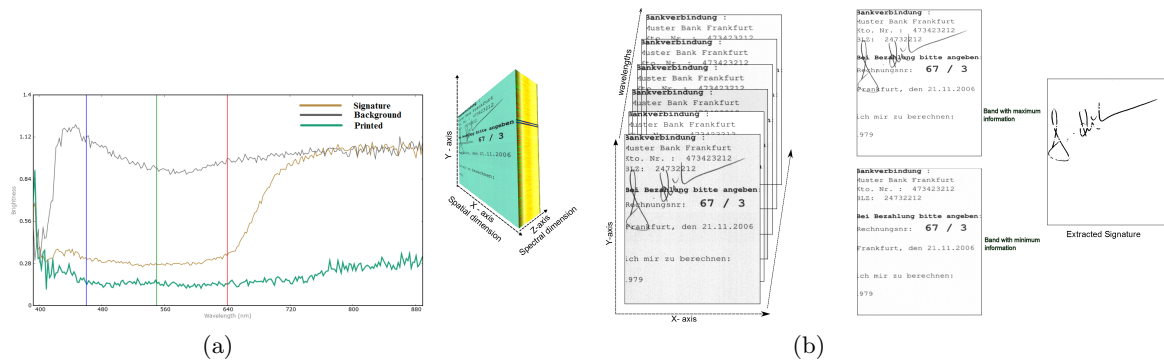


Figure 2. (a) Spectral Response: Background, Printed, and Signature pixels. (b) Signature Segmentation: Methodology.

- Recall: the measure which represents if the system has retrieved all the signatures from a document.

Table 1. Signature Segmentation results

Metric	Value%
<i>Precision</i>	100
<i>Recall</i>	73

4. Open Issues and Ongoing Research

We have presented the state-of-the-art of automatic information extraction methods (particularly, for signatures) from document images. Most of the today’s automatic signature verification systems can not be applied directly for document authentication in the real world scenarios. This is because in such scenarios signatures are mostly available on documents, e.g., bank checks, forms, and wills, etc., with other information like, background text, lines, and logos. We argue that to perform verification in the real world especially forensic cases, first segmentation of signatures is required. Further, signatures can be found at different locations in different documents (as shown in Figure 1). Therefore, a layout free extraction of signatures is needed (as proposed in the above section). Such systems would find signatures without using priori information about the layout of the document under examination and/or probable location of signatures.

In order to have good segmentation systems that are integrable with signature verification system so that to be effectively usable in real world, it is a must to first have some benchmark datasets. These datasets would then be used to evaluate newly proposed and existing signature segmentation system in terms of their precision and recall as well as performance and quality of extraction. As mentioned earlier, we are already working on development of such a dataset and so far have developed a dataset of 100 HSI scanned documents. Currently this data has patch level information about where signatures are located, we plan to provide signature stroke information and that would be usable for testing complete signature segmentation and verification frameworks for analysis of documents containing signatures.

An improvement in the current signature verification systems can be to enable them distinguish genuine and forged signatures even in the presence of some noise in signature, e.g., touching characters or missing part of signatures (as appeared in the proposed technique). Figure 1 (d) shows a very common scenario where most of the existing signature systems will misclassify these signatures as forgery, as they assume that questioned signatures contain no information other than signatures.

Finally, the use of local features has already shown promising results in signature verification where verification is performed on the basis of parts of signatures rather than considering the complete structure of signature (Liwicki and Malik (2011)). It is assumed, in general, that the systems with local features have potential to perform well in presence of noise due to segmentation or background and therefore should be integrable with signature segmentation systems.

References

Aalderink, B., M. Klein, R. Padoan, G. De Bruin and T. Steemers. 2009. Clearing the Image: A Quantitative Analysis of Historical Documents Using Hyperspectral Measurements. In *37th AIC*.
 Ahmed, Sheraz, Muhammad Imran Malik, Marcus Liwicki and Andreas Dengel. 2012. Signature Segmentation from Document Images. In *ICFHR*. IEEE. 423-427.
 Banerjee, Purnendu and Bidyut Baran Chaudhuri. 2012. A System for Hand-Written and Machine-Printed Text Separation in Bangla Document Images. In *ICFHR*. IEEE.

- Brauns, Eric B and R Brian Dyer. 2006. "Fourier transform hyperspectral visible imaging and the nondestructive analysis of potentially fraudulent documents." *Applied spectroscopy* 60(8):833–840.
- Chanda, Sukalpa, Katrin Franke and Umapada Pal. 2010. Structural handwritten and machine print classification for sparse content and arbitrary oriented document fragments. In *ACM-SAC*. pp. 18–22.
- Djeziri, S., F. Nouboud and R. Plamondon. 1998. "Extraction of signatures from check background based on a filiformity criterion." *TIP* 7(10):1425–1438.
- Goltz, Douglas, Michael Attas, Gregory Young, Edward Cloutis and Maria Bedynski. 2010. "Assessing stains on historical documents using hyperspectral imaging." *Journal of Cultural Heritage* 11(1):19–26.
- Guo, J.K. and M.Y. Ma. 2001. Separating handwritten material from machine printed text using hidden Markov models. In *ICDAR*. pp. 439–443.
- Hunt, Robert William Gainer. 2005. *The reproduction of colour*. John Wiley & Sons.
- Imade, S., S. Tatsuta and T. Wada. 1993. Segmentation and classification for mixed text/image documents using neural network. In *ICDAR*. pp. 930–934.
- Jayadevan, R., S.R. Kolhe, P.M. Patil and U. Pal. 2012. "Automatic processing of handwritten bank cheque images: a survey." *IJDAR* 15:267–296.
- Khan, Z., F. Shafait and A. Mian. 2013. Hyperspectral Imaging for Ink Mismatch Detection. In *ICDAR*. pp. 877–881.
- Kuhnke, K., L. Simoncini and Zs.M. Kovacs-V. 1995. A system for machine-written and hand-written character distinction. In *ICDAR*. Vol. 2 pp. 811–814 vol.2.
- Leutenegger, Stefan, Margarita Chli and Roland Yves Siegwart. 2011. BRISK: Binary robust invariant scalable keypoints. In *ICCV*. IEEE pp. 2548–2555.
- Liwicki, Marcus and Muhammad Imran Malik. 2011. Surprising? Power of Local Features for Automated Signature Verification. In *IGS*. pp. 18–21.
- Lowe, D.G. 1999. Object recognition from local scale-invariant features. In *ICCV*. pp. 1150–1157.
- Madasu, Vamsi Krishna, Mohd Hafizuddin, Mohd Yusof, M. Hanm and Lu Ss. 2003. Automatic extraction of signatures from bank cheques and other documents. In *DICTA*. pp. 591–600.
- Malik, M. I., Marcus Liwicki, Andreas Dengel and Bryan Found. 2013. Man vs. Machine: A Comparative Analysis for Forensic Signature Verification. In *IGS*. International Graphonomics Society pp. 9–13.
- Malik, Muhammad Imran, Marcus Liwicki and Andreas Dengel. 2013. Part-based automatic system in comparison to human experts for forensic signature verification. In *ICDAR*. IEEE pp. 872–876.
- Mandal, Ranju, Partha Pratim Roy and Umapada Pal. 2011. "Signature Segmentation from Machine Printed Documents Using Conditional Random Field." *ICDAR* 0:1170–1174.
- Mandal, Ranju, Partha Pratim Roy and Umapada Pal. 2012. "Signature Segmentation From Machine Printed Documents Using Contextual Information." *IJPRAI*.
- Morales, A., M. Ferrer, M. Diaz-Cabrera, C. Carmona and G. Thomas. 2014. The use of hyperspectral analysis for ink identification in handwritten documents. In *ICCST*. IEEE pp. 1–5.
- Mozaffari, Saeed and Parnia Bahar. 2012. Farsi/Arabic Handwritten from Machine-printed Words Discrimination. In *ICFHR*. IEEE.
- Reed, G, K Savage, D Edwards and N Nic Daeid. 2014. "Hyperspectral imaging of gel pen inks: An emerging tool in document analysis." *Science & Justice* 54(1):71–80.
- Rosten, Edward and Tom Drummond. 2005. Fusing points and lines for high performance tracking. In *ICCV*. Vol. 2 pp. 1508–1515 Vol. 2.
- Sankari, M., M. Benazir and R. Bremananth. 2010. Verification of bank cheque images using Hamming measures. In *ICARCV 10*. pp. 2531–2536.
- Shiel, P., M. Rehbein and J. Keating. 2009. "The ghost in the manuscript: Hyperspectral text recovery and segmentation." *Codicology and Palaeography in the Digital Age* pp. 159–174.
- Silva, C., M. Pimentel, R. Honorato, C. Pasquini, J. Prats-Montalbán and A. Ferrer. 2014. "Near infrared hyperspectral imaging for forensic analysis of document forgery." *Analyst* 139(20):5176–5184.
- Wyszecki, G and WS Stiles. 1982. "Color science: Concepts and methods, quantitative data and formulae. 1982." *John Wiley&Sons, New York*.
- Zheng, Yefeng, Huiping Li and D. Doermann. 2004. "Machine printed text and handwriting identification in noisy document images." *TPAMI* 26(3):337–353.
- Zhu, Guangyu, Yefeng Zheng, David Doermann and Stefan Jaeger. 2007. *Multi-scale Structural Saliency for Signature Detection*. Minneapolis, MN pp. 1–8.
- Zhu, Guangyu, Yefeng Zheng, David Doermann and Stefan Jaeger. 2009. "Signature Detection and Matching for Document Image Retrieval." *TPAMI* 31(11):2015–2031.

Stability/Complexity Analysis of Dynamic Handwritten Signatures

Giuseppe PIRLO^(a), Donato IMPEDOVO^(b), Tommaso FERRANTI ^(a)

^(a) *Dipartimento di Informatica - Università degli Studi di Bari, via Orabona, 4, 70125, Bari, ITALY*

^(b) *Dipartimento di Informatica, Elettrotecnica ed Elettronica - Politecnico di Bari, via Amendola 126
70125, Bari, ITALY*

{corresponding author: giuseppe.pirlo@uniba.it}

Abstract. This paper presents an experimental investigation on stability and complexity of dynamic signatures. A technique based on multiple matching strategies using Dynamic Time Warping is considered to derive both stability and complexity information from dynamic signatures. The experimental results, carried out on signatures of the SUSIG database, highlight some interesting characteristics on handwritten signatures.

1. Introduction

Although research community performed many efforts in the field of automatic signature verification, the concrete applicability of a signature verification system in daily-life applications is still difficult. The main reason is that handwritten signature is the product of a very complex generation process that depends on the psychophysical state of the signer and the conditions under which the signature apposition process occurs (Plamondon and Guerfali, 1998; Djioa and Plamondon, 2009).

In order to understand better the complex phenomena underlying the signing process several studies have been devoted more recently to the analysis of the signing process, and particularly on variability and complexity of dynamic signatures. This research can provide useful insights not only for the development of more effective systems for automatic signature verification but also for supporting the use of handwritten signatures for other applications like those devoted to analysis of health conditions and diagnosis of neurodegenerative diseases (Plamondon et al., 2014).

In the literature, approaches for the analysis of stability in handwritten signatures can be grouped into three categories: model-based, feature-based and data-based. When model-based approaches are considered, signature are first described by a model and successively, model parameter are evaluated to extract information of signature characteristics. One of the main model-based approach uses a Hidden Markov Model (HMM) for computing a stability measure to group and characterize dynamic signatures in classes that can be assigned to signature variability and complexity (Garcia-Salicetti et al., 2008). This measure has been used to determine whether a signature does or does not contain enough information to be successfully processed by a verification system (Houmani et al., 2009). When feature-based approaches are considered, signature stability is estimated by the analysis of a specific set of characteristics. One feature-based technique for estimating local stability in static signatures first segmented the signature images using an equimass approach. Successively, a multiple-matching strategy was applied in which feature vectors extracted from corresponding regions of genuine specimens were matched through cosine similarity (Pirlo and Impedovo, 2013a). When considering dynamic signatures, a comparative study using a distance-based consistency model on features demonstrated that pen position, velocity and inclination have the highest consistency. In addition, other results have demonstrated that position is a stronger characteristic than pressure and pen inclination when personal entropy is considered (Lei and Govindaraju, 2005). Data-based approaches use raw data to perform the analysis of signature stability. When static signatures are considered, the stability of each region of a signature can be estimated by a multiple pattern-matching strategy (Impedovo et al., 2009). The basic idea is to match corresponding regions of genuine signatures in order to estimate the extent to which they are locally different. A preliminary step is used to determine the best alignment of the corresponding regions of signatures in order to diminish any differences among them. Another approach considers that, given a genuine signature, any other genuine specimen can be considered as the result of a deformation process that can be analyzed with an optical flow. Therefore, the analysis of the optical flow obtained by matching the genuine signatures with other genuine specimens can provide information about the local stability in the signature image useful for signature verification (Pirlo and Impedovo, 2013b). When dynamic signatures are considered, the stability regions of signatures can be defined as the longest similar sequences of strokes between a pair of genuine signatures (Parziale et al., 2013). This definition is based on the assumption that signing is the automated execution of a well-learned motor task and, therefore, repeated executions should ideally produce similar specimens. However, variations in signing conditions can lead to signatures that differ only locally due to short sequences of strokes that exhibit different shapes. Another approach estimates a local stability function of dynamic signatures by using Dynamic Time Warping (DTW) to match a genuine signature with other authentic specimens (Impedovo et al., 2012). In this method, each matching is used to identify what are called Direct Matching Points (DMPs), i.e., unambiguously matched points of the genuine signature. Thus, a DMP can indicate the presence of a small stable region of the signature since no significant distortion can be detected locally. Furthermore, the local stability value associated with a point of a signature is determined as the average number of times it is a DMP when the signature is matched against other genuine signatures.

Signature complexity has been a field of specific research since it is generally argued that the complexity of a signature can be critical to the reliability of the examination process (Huber and Headrick, 1999). Notwithstanding no common

meaning of handwriting complexity was defined yet. In general, in signature analysis, signature complexity can be thought to be an estimator of the difficulty for its imitation. Signature complexity can be obtained as the result of the difficulty in perceiving, preparing and executing each stroke of the signature itself (Brault and Plamondon, 1993). A complexity theory, which is based on the theoretical relationship between the complexity of features of the handwriting process and the number of concatenated strokes, was also considered for complexity estimation. According to this theory signature complexity can be estimated by analyzing variables that indirectly relate to the number of concatenated strokes, like for instance the number of turning points, the number of feathering points, and the number of intersections and retraces (Found and Rogers, 1995).

In this paper the approach based on Dynamic Time Warping that uses a genuine-to-genuine matching strategy for the analysis signature stability, is also considered in a genuine-to-forgery matching strategy for estimating signature complexity. Successively, stability/complexity information is used to extract general information from signers of the SUSIG database.

2. A General Approach for Stability/Complexity Analysis

Let

$$S = \{S_1, S_2, \dots, S_n, \dots, S_N\} \quad (1)$$

be a set of N genuine signatures. In this paper, each signature S_n is considered as a sequence of elements $S_n = (z_n^1, z_n^2, \dots, z_n^i, \dots, z_n^M)$, where each element z_n^i is a 4-tuple $z_n^i = (x_n^i, y_n^i, t_n^i, p_n^i)$, with: - x_n^i and y_n^i : coordinates of the pen on the writing plane; - t_n^i : timestamp; - p_n^i : pressure.

After data acquisition, the first stage is preprocessing, that consisted of value normalization and length normalization. Value normalization was performed for each signature according to the linear normalization algorithm so that each value was reported in the range [0,1]. Similarly, signature length normalization was performed using the linear interpolation algorithm that made the length of all signatures equal to M (in our case M=256). Successively, four function features were extracted in the feature extraction step:

1) Displacement (s)

- $s^i = \sqrt{(x^{i+1} - x^i)^2 + (y^{i+1} - y^i)^2}$ $i=1,2,\dots,M-1$
- $s^M = s^{M-1}$

2) Velocity (v)

- $v^i = \frac{s^i}{(t^{i+1} - t^i)}$, $i=1,2,\dots,M-1$
- $v^M = v^{M-1}$

3) Acceleration (a)

- $a^i = \frac{v^i}{(t^{i+1} - t^i)}$, $i=1,2,\dots,M-1$
- $a^M = a^{M-1}$

4) Pressure (p). In this case no conversion is necessary with respect to the acquired data in the pressure domain.

Therefore, this procedure allowed the conversion of the signature representation domains from the space of the 4-tuples (x,y,t,p) to the space of the 4-tuples (s,v,a,p) .

3. Estimating Stability/Complexity of Dynamic Signatures

For the analysis of stability of dynamic signatures we assume that each signature S_n of the set (1) was a genuine signature and was represented by a sequence of elements

$$S_n = (z_n^1, z_n^2, \dots, z_n^i, \dots, z_n^M) \quad (2)$$

where each element z_n^i is a 3-tuple (v_n^i, a_n^i, p_n^i) , with: - v_n^i : velocity; - a_n^i : acceleration; - p_n^i : pressure.

Now, let S_r, S_t be two signatures of the set (1), a warping function between S_r and S_t was any sequence of couples of indexes identifying points of S_r and S_t to be joined (Impedovo et al., 2012):

$$W(S_r, S_t) = c_1, c_2, \dots, c_K \quad (3)$$

where $c_k=(i_k, j_k)$ (k, i_k, j_k integers, $1 \leq k \leq K$, $1 \leq i_k \leq M_i$, $1 \leq j_k \leq M_j$). Now, if we consider a distance measure $d(c_k)=d(z^{i_k}, z^{j_k})$ between points of S_r and S_t , we can associate to $W(S_r, S_t)$ the dissimilarity measure

$$D_{w(S_r, S_t)} = \sum_{k=1}^K d(c_k) \quad (4)$$

The elastic matching procedure detected the warping function $W^*(S_r, S_t) = c^*_1, c^*_2, \dots, c^*_K$ which satisfied the monotonicity ($i_1 \leq i_2 \leq \dots \leq i_{K-1} \leq i_K$ and $j_1 \leq j_2 \leq \dots \leq j_{K-1} \leq j_K$), continuity ($i_k - i_{k-1} \leq 1$ and $j_k - j_{k-1} \leq 1$, for $k=2,3,\dots,K$) and boundary ($c_1=(1,1)$, $c_K=(M,M)$) conditions, and for which it was found to be:

$$D_{W^*(S_r, S_t)} = \min_{W(S_r, S_t)} D_{W(S_r, S_t)}. \quad (5)$$

From $W^*(S_r, S_t)$ we identified the *Direct Matching Points* (DMP) of S_r with respect to S_t . A DMP of a signature S_r with respect to S_t was a point which had a one-to-one coupling with a point of S_t . In other words, let z^p_r be a point of S_r coupled with z^q_t of S_t ; z^p_r is the DMP of S_r with respect to S_t if:

- (a) $\forall \bar{p} = 1, \dots, M$, $\bar{p} \neq p$, yields: $z^{\bar{p}}_r$ is not coupled with z^q_t ;
- (b) $\forall \bar{q} = 1, \dots, M$, $\bar{q} \neq q$, yields: $z^{\bar{q}}_t$ is not coupled with z^p_r .

A DMP indicates the existence of a region of the r-th signature which is roughly similar to the corresponding region of the t-th signature (in the domain d specified by the distance used for the elastic matching procedure). Therefore, for each point of S_r , a score was introduced according to its type of coupling with respect to the points of S_t (Huang and Yan, 2003):

$$\text{Score}^t(z^{p_{d,r}}) = 1 \quad \text{if } z^{p_{d,r}} \text{ is a DMP, } 0 \text{ otherwise} \quad (6)$$

The local stability function of S_r was defined as (Huang and Yan, 2003):

$$I(z^{p_{d,r}}) = \frac{1}{N-1} \sum_{\substack{t=1 \\ t \neq r}}^N \text{Score}^t(z^{p_{d,r}}). \quad (7)$$

In our study, we compute the stability function by considering the signature S_1 of the set (1) for reference. Therefore the stability function in the d domain for the set (1) is assumed to be

$$I^{\text{stab}}(z^{p_{d,1}}) = I(z^{p_{d,1}}). \quad (8)$$

Following the same approach, if we assume that S_1 is genuine and S_t , $t=2,3,\dots,n$, are forgeries, we can compute using eq. (5) the complexity function:

$$I^{\text{compl}}(z^{p_{d,1}}) = I(z^{p_{d,1}}). \quad (9)$$

In fact, the score of eq. (4) in this case identifies the existence of a small region of the r-th signature that is quite easy to imitate for a forger. Thus, in this approach, complexity of a signature can be considered as a measure of difficulty to forge the signature.

4. Experimental Results

In this paper, handwritten signatures of the SUSIG ‘‘Visual subcorpus’’ database were used to perform stability/complexity analysis (Kholmatov and Yanikoglu, 2009). Precisely, in this work, 11 genuine signatures (the signature S_1 and 10 genuine signatures S_2, S_3, \dots, S_{11} for computing stability) and 10 forgeries (10 counterfeit signatures S_2, S_3, \dots, S_{11} for computing complexity) of each one of the 100 signers enrolled in the database were considered. Figure 1 shows the stability of a signer indicated by different colors: green \rightarrow low stability regions; yellow \rightarrow medium stability regions; red \rightarrow high stability regions.

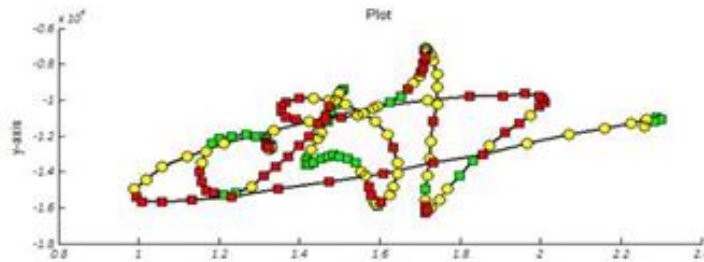


Figure 1. Levels of stability/complexity .

Successively, regional analysis of handwritten signatures was performed. Each signature was divided into three parts of equal length: initial, medium and final. Stability and complexity of each part were computed. Figure 2 shows the average value of stability and complexity for each part of the signature. The result shows that, in general, there is a direct correlation between stability and complexity in each region of the signature. In addition, initial and central parts of signatures are generally the most stable and complex.

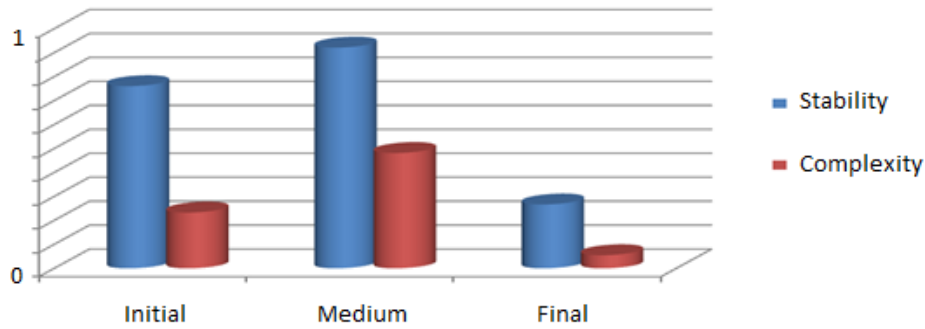


Figure 2. Stability/complexity in dynamic signatures: a regional analysis.

5. Conclusion

This paper presents a stability/complexity analysis of dynamic signatures using a multiple matching strategy. The approach allows to understand better the processes underlying signature apposition and also can provide useful insights for the design of more rational and effective signature verification techniques. Based on this approach, some directions for further investigation can be addressed. In particular, this research offers new insights for the recognition of relevant parts of handwriting, with specific characteristics in terms of stability/complexity, that can be used effectively for the development of the handwriting-based biometrics systems.

References

- J.-J. Brault and R. Plamondon, 1993, A Complexity Measure of Handwritten Curves: Modeling of Dynamic Signature Forgery, *IEEE Transactions on Systems, Man, and Cybernetics*, Vol. 23, No. 2, pp. 400-413.
- M. Djioua and R. Plamondon, 2009, A New Algorithm and System for the Characterization of Handwriting Strokes With Delta-Lognormal Parameters, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 31, No. 11, pp. 2060-2072.
- B. Found and D. Rogers, 1995, Contemporary issues in forensic handwriting examination. A discussion of key issues in the wake of the Starzecpyzel decision, *Journal of Forensic Document Examination*, Vol. 8, pp.1-31.
- S. Garcia-Salicetti, N. Houmani, B. Dorizzi, 2008, A client-entropy measure for on-line signatures, *Proceedings of the IEEE Biometrics Symposium*, Tampa, USA, pp. 83-88.
- N. Houmani, S. Garcia-Salicetti, B. Dorizzi, 2009, On assessing the robustness of pen coordinates, pen pressure and pen inclination to time variability with personal entropy, *Proc. of IEEE 3rd International Conference on Biometrics: Theory, Applications, and Systems*, Washington, DC, pp. 1-6.
- K. Huang and H. Yan, 2003, Stability and style-variation modelling for on-line signature verification, *Pattern Recognition*, Vol. 36, No. 10, pp. 2253-2270.
- R.A. Huber and A.M. Headrick, 1999, *Handwriting identification: facts and fundamentals*, Boca Raton: CRC Press.
- D. Impedovo, G. Pirlo, E. Stasolla, C.A. Trullo, 2009, Learning Local Correspondences for Static Signature Verification, *Proc. 11th Int. Conf. of the Italian Association for Artificial Intelligence*, Italy.
- D. Impedovo, G. Pirlo, L. Sarcinella, E. Stasolla, C.A. Trullo, 2012, Analysis of Stability in Static Signatures using Cosine Similarity, *Proc. XIII International Conference on Frontiers in Handwriting Recognition (ICFHR 2012)*, Monopoli, Bari (Italy), pp. 231-235.
- H. Lei and V. Govindaraju, 2005, A comparative study on the consistency of features in on-line signature verification, *Pattern Recognition Letters*, Vol. 26, pp. 2483-2489.
- A. Parziale, S. Fuschetto, A. Marcelli, 2013, Exploiting stability regions for online signature verification, *Proceedings Workshop on Emerging Aspects of Handwritten Signature Processing*, Springer-Verlag, Vol. 8158, pp. 112-121.
- G. Pirlo and D. Impedovo, 2013(a), Cosine similarity for analysis and verification of static signatures, *IET Biometrics*, Vol. 2, No. 4, pp. 151-158.
- G. Pirlo and D. Impedovo, 2013(b), Verification of Static Signatures by Optical Flow Analysis, *IEEE Transactions on Human-Machine Systems*, Vol. 43, No. 5, pp. 499-505.
- R. Plamondon and W. Guerfali, 1998, The generation of handwriting with delta-lognormal synergies, *Biological Cybernetics*, Vol. 78, No. 2, pp. 119-132.
- R. Plamondon, G. Pirlo, D. Impedovo, 2014, Online Signature Verification, *Handbook of Document Image Processing and Recognition*, D. Doermann & K. Tombre (eds.), Springer, pp. 917-947.

Characteristics of Constrained Handwritten Signatures: An Experimental Investigation

Donato IMPEDOVO^(a), Giuseppe PIRLO^(b), Fabrizio RIZZI^(b)

^(a)*Dipartimento di Informatica, Elettrotecnica ed Elettronica - Politecnico di Bari, via Amendola 126
70125, Bari, ITALY*

^(b)*Dipartimento di Informatica - Università degli Studi di Bari, via Orabona, 4
70125, Bari, ITALY*

{corresponding author: giuseppe.pirlo@uniba.it}

Abstract. Handwritten signatures are considered one of the most useful biometric traits for personal verification. In the networked society, in which a multitude of different devices can be used for signature acquisition, specific research is still needed to determine the extent to which features of an input signature depend on the characteristics of the signature apposition process.

In this paper an experimental investigation was carried out on constrained signatures, which were acquired using writing boxes having different area and shape, and the different behaviour of dynamic features with respect to the writing boxes are discussed.

1. Introduction

Handwritten signature is one of the most common biometric traits for personal authentication. A signature is a rapid movement that is defined, learned and practiced over the youth years to become a person's peculiar identifying pattern. It originates from a complex process that involves the human brain to process information to perform with the human writing system (based on hand, arm, etc.), using writing acquisition equipment (pen, pencil, paper, etc.). Therefore, it is not surprising that - in recent years - many efforts have been devoted to automatic signature verification, attracting researchers from different fields. More precisely, so far research efforts have been mainly devoted to determine effective features and comparison strategies for signature verification (Impedovo and Pirlo, 2008).

Concerning features, both functions and parameters were considered in the literature. When function-features are used, the signature is characterized by a time-function, whose values constitute the feature set. Among others, widely used functions features are position, velocity, acceleration and pressure. When parameter-features are used, a signature is characterized as a vector of parameters, each one representative of the value of a feature. Among others, widely considered parameters are total signature time duration, pen-down time ratio, number of pen-lifts, direction- and curvature-based features.

When comparison strategies are considered, both distance-based and model-based approaches have been widely investigated in the literature. Concerning distance-based verification techniques, Mahalanobis and Euclidean distances have been used for signature comparison as well as Dynamic Time Warping (DTW) and string matching strategies. When model-based techniques are considered, Hidden Markov Models (HMM) have found to be well-suited for signature modelling since they are highly adaptable to personal variability and lead to results that are - in general - superior to other signature modelling techniques (Plamondon et al. 2014).

Notwithstanding several relevant results have been achieved so far, many aspects still remains to be investigated, in order to make signature verification feasible in a multitude of daily operations. Among the others, one of the most relevant open aspects concerns the relation between the constraints during the signature apposition process and the characteristics of the input signature. In fact, signers can use different devices (tablet, smartphone, PDA, etc.) to input their signatures and hence the verification system must be aware of the differences in the input signatures due to the acquisition conditions (Simsons, 2011).

In this paper we perform an experimental investigation on signatures acquired under constrained conditions. More precisely, the relations between some dynamic features of the input signature and size and shape of the writing area are analysed. The experimental results demonstrate that, in general, velocity is highly dependent on the writing area, whereas acceleration is low dependent on the writing area.

The organization of the paper is the following. Section 2 presents the experimental setup. Section 3 reports the experimental results. Section 4 addresses the conclusion of the paper and some considerations for future work.

2. Experimental Setup

The experimental setup was realized using a Wacom Intuos3 tablet and an Intuos3 Grip Pen. The Intuos3 Grip Pen is a cordless, battery-free and pressure-sensitive freehand writing device [5]. Macros on the Wacom Intuos3 tablet ensure that the area of signature was positioned in the centre of the tablet in order to maximize comfort and sensitivity of the user. Five conditions were considered to represent some common area and shape constraints in signature apposition:

- a) 4.6cm x 0.77cm rectangular box (to analyse the effect of constriction in small boxes);
- b) 7.0cm x 1.5cm rectangular box (space-like signatures of the identity card and bank checks);
- c) 14cm x 2cm rectangular box
- d) 12cm x 7cm rectangular box (to see the biggest change of signature);
- e) 12cm guideline (that is present for signature apposition on several administrative forms)

Figure 1 shows the five types of constraints that were considered for signature apposition in this paper. During the enrolment stage, 15 signers have been involved in data acquisition. For each type of constraint, six signatures were captured from each signer. Therefore, each signer collected a total number of $6 \times 5 = 30$ genuine signatures. During testing the signer sat down and wrote comfortably, with a sheet of paper placed on the tablet to increase comfort and truthfulness.



Figure. 1a: rectangular box (4.6cm x 0.77cm)



Figure. 1b: rectangular box (7.0cm x 1.50cm)



Figure. 1c: rectangular box (14.0cm x 1.50cm)



Figure. 1d: rectangular box (12.0cm x 7.0cm)



Figure. 1e: guideline (12.0cm)

Before the acquisition process, each participant filled an anonymous questionnaire concerning personal information: age, sex, education level, writing mode (right or left hand). The results, reported in Table 1, showed the homogeneity of participants, with a slight predominance of males, mostly included in the group of 20-40 years old subjects. Almost all of the subjects were right handed.

Table 1. Database: Characteristics of the Signers

Characteristic	Feature	Percentage
Sex	Male	60%
	Female	40%
Age	16 – 20 years old	26%
	20 – 40 years old	60%
	More than 40 years old	14%
Education Level	5 years (elementary school level)	6%
	8 years education	20%
	13 years education	40%
	More than 16 years (University Level)	34%
Writing Mode	Right - Hand	94%
	Left - Hand	6%

3. Experimental Results

For the analysis of the experimental data, the MovAlyzeR suite was used. The suite contains ScriptAlyzeR™ that can transform a tablet, a mouse or a pen in a high quality system for the measurement of hand-based writing movements. Using MovAlyzeR the experiment was divided in three sub-phases: "Groups", with reference to the number of the test, "Subject", that concerns the identification number (ID) of each one of the fifteen participants, and "Constraints", that concerns the identification code (IC) of each one of the five writing constraints (see Figure 1).

The data collected through MovAlyzeR were analysed in order to determine statistical differences in the following dynamic features:

- Velocity in the vertical direction (V_y)
- Velocity in the horizontal direction (V_x)
- Acceleration in the vertical direction (A_y)
- Acceleration in the horizontal direction (A_x)
- Pressure in the vertical direction (P_y)
- Pressure in the horizontal direction (P_x).

For each signer the analysis of variance among the five groups of constrained signatures was performed. For the purpose the ANOVA test was considered (Gelman, 2005). ANOVA starts from the assumption that for G groups of data, it is possible to decompose the variance into two components: the variance inside the groups and the variance between groups. From these values, calculated as the sums of the standard deviations between the groups and within a single group, we can get a test variable for comparison with the value of a variable Fisher "F", taking into account the degrees of freedom, according to the significance level α to evaluate the results.

Table 2 reports, for each signer and each dynamic feature, the results of the ANOVA test (with $\alpha = 0.05$ in our tests), where: "D" – Dependent; "ND" – Not Dependent. Velocity seems to be the feature that mostly depends on the size/shape constraints of the writing area. All users have changed the writing velocity to adapt the signing process to the writing space. In general we observed low velocity in small boxes and high velocity in large boxes. The analysis of pressure and acceleration, instead, demonstrate no general behaviour of signers. For these two characteristics, it seems the behaviour of signers not to change significantly due to constraint of the writing area.

Table 2. Dependence of Dynamic Features from Constraints in Signature Acquisition

User	Vy	Vx	Ay	Ax	Py	Px
1	D	D	ND	ND	ND	ND
2	D	D	ND	D	ND	D
3	D	D	ND	D	ND	D
4	D	ND	ND	ND	D	D
5	D	D	ND	ND	ND	ND
6	D	D	ND	ND	D	ND
7	D	D	ND	ND	ND	ND
8	D	D	ND	ND	D	ND
9	D	D	ND	D	ND	ND
10	D	D	ND	D	ND	ND
11	D	D	ND	ND	ND	D
12	D	D	ND	D	ND	ND
13	D	ND	ND	ND	D	D
14	D	D	ND	ND	ND	ND
15	D	D	ND	ND	ND	D

4. Conclusion and Future Work

This paper presents an experimental investigation on the effects of the characteristics of the writing area on the dynamic features of online signatures. For the purpose five different signature acquisition areas were considered (which differ in terms of area and shape) for signature acquisition and the ANOVA test were applied to verify to what extent dynamic features of a signature are depends on the writing area. The experimental results demonstrate that velocity seems to be very dependent on the writing area whereas acceleration and pressure behaviour depends on the specific signer.

Although this study is not sufficient to derive general assumption on the characteristics of constrained online signatures, it poses new interesting problems to the scientific community both for improving the knowledge on human behaviour in signing and for improving future systems for automatic signature verification. Among the others, an interesting aspect for assuring interoperability of signature verification systems could be the possibility to develop new (signer-dependent or signer-not dependent) techniques for dynamic features normalization for constrained signature.

References

- A. Gelman, 2005, Analysis of variance? Why it is more important than ever, *The Annals of Statistics*, Vol. **33**, pp. 1–53.
- D. Impedovo, G. Pirlo, Sept. 2008, Automatic Signature Verification – State of the Art, *IEEE Transactions on Systems, Man and Cybernetics - Part C: Applications and Review*, vol. 38, no. 5, pp. 609 – 635.
- R. Plamondon, G. Pirlo, D. Impedovo, 2014, Online Signature Verification, in *Handbook of Document Image Processing and Recognition*, Doermann, D. & Tombre, K. eds., Springer, pp. 917-947.
- D. Simsons, R. Spencer, S. Auer, June 2011, The Effects of Constraining Signatures. *Journal of the American Society of Questioned Document Examiners*, Vol. 14, No. 1, pp. 39-50.

Handwriting and Visual Impairment: A Forensic Analysis of J. S. Bach's Signatures

Heidi H. HARRALSON ^a, Clare KAUFMAN ^b and Martin W. B. JARVIS ^c

^a East Tennessee State University, Johnson City, Tennessee, USA

^b Institute of Optometry, London, United Kingdom

^c Charles Darwin University, Darwin, Australia

^a spectrum008@aol.com, ^b clarekaufman@gmail.com, ^c martin.jarvis@cdu.edu.au

Abstract. This paper examines the historical signatures of 18th century composer, J. S. Bach, to evaluate the effects of vision impairment on handwritten signatures. It is questioned whether Bach penned certain signatures as it is historically documented that he was virtually blind in the years just prior to his death in 1750. Applying information collected from published forensic studies about the effects of vision impairment on handwriting, handwriting indices of vision impairment are compared to Bach's signatures in the late 1740s.

1. Introduction

Forensic handwriting examination techniques have been previously utilized in the examination of music calligraphy associated with J. S. Bach (1685-1750) manuscripts. Notably, Jarvis (2007) postulated that the music calligraphy on some manuscripts historically associated with J. S. Bach were written by his wife, Anna Magdalena Bach. In furthering research concerning the authorship of Bach manuscripts and specifically signatures on manuscripts and letters, forensic handwriting examination techniques were applied in the analysis of purported J. S. Bach signatures written late in his life when he was suffering from severe eye strain and eye surgeries which eventually contributed to his death in 1750. This paper presents the results of an examination of J. S. Bach's signatures during the decade in his life associated with severe eye strain and eye surgeries. The observations of Bach's signatures from the 1740s are compared to information associated with visual impairment and its manifestation in handwriting as published in forensic literature.

2. Literature Review: Bach's Vision

Historically, it is believed by many scholars that the source of Bach's eyesight problems can be traced back to the period when in 1695 he went, at age ten, to live with his brother Johann Christoph Bach, following the death of his parents (EWB, 2015). During this period it is generally accepted that he was in the habit of copying manuscripts out by moonlight, thereby causing severe eye strain, that was then to be with him for the remainder of his life (NNDB, 2014; Gramophone, 2015). Evidence for this comes from his portrait "where Bach appears to squint, and the way his facial muscles are aligned has led analysts to believe that he suffered from shortsightedness [myopia]....Yet, according to his son [Carl Philipp Emanuel's Obituary of his father (David et al., 1999)], his eyesight was always weak; and according to his first biographer, Forkel (1802), he had a 'very painful disorder in the eyes'" (Ho, 2010).

It would seem that Bach had "naturally bad vision" and that "this was further weakened by a lot of studying, sometimes even all night long, especially during his youth" (Zegers, 2005, p. 1428). From his symptoms Zegers also suggests that he was myopic, although only moderately. He thinks that his possible level of refractive error was about -2.00 D; if it had been greater he would not have been able to play the organ in church. Zegers states that even recognising people's faces in the street would have been difficult with Bach's level of myopia, unless he wore his spectacles.

Refractive error is defined as "a defect in the ability of the lens of the eye to focus an image accurately, as occurs in nearsightedness [myopia] and farsightedness [hyperopia]" (Mosby's Medical Dictionary, 2009). Refractive error is important as, if it is left uncorrected, can cause avoidable visual impairment. There is some evidence to suggest that children who do a great deal of close work may either become myopic or make a pre-existing condition worse although a recent review notes that evidence for this is equivocal (Foster & Jiang, 2014). The review commented that greater time spent outdoors might be associated with reduced myopia.

It seems that Bach had a strong physical constitution throughout his life. However, he appears to be physically obese in the Hausmann portrait of 1748 and that "[a] striking feature is the narrowed eyelids. A closer look seems to give the impression of dermatochalasis ["sagging of the eyelid skin and underlying muscle that occurs commonly during the aging process" (dictionary.reference.com/medical)]; this has no serious clinical implications except that it can sometimes restrict the superior visual field" (Zegers, 2005, p. 1428). According to Bach's contemporaries his vision deteriorated as he aged. As his myopia was only mild, Zegers has concluded that the most likely cause of his visual difficulty was cataract. A cataract is defined as: "The development of an opacity within the lens. As we age, there is a disturbance in the structure of the lens and accumulation of pigment. The clarity of the normal lens is maintained through a precise structural arrangement of fibres and

balance of chemical constituents. This change to the microstructure results in opacification, which consequently alters the penetration and refraction of light...Clouding of the lens will cause a degree of scattering of light rather than focusing it to a point on the retina. The more opaque it becomes, the greater the scatter and the worse the vision. The majority of cataracts are age related" (Nash, 2013, p. 555).

The symptoms of age related cataract include: visual difficulty in dim light, needing more light to see things clearly, difficulty in reading small and fine print, alteration in colour perception and everything may have a yellow or brown tinge, spectacles become less effective, patients may see halos around bright lights and some experience double vision (NHS, 2015). Living in 18th century Germany, Bach would have worked by candle-light and, particularly during the autumn and winter months, he would have also experienced naturally lower levels of light. This would have had a greater impact on his vision as he aged, i.e. the developing cataract would have caused increasing difficulties seeing the lines on manuscript paper and writing on them accurately.

Up until about 1750, the only treatment for cataracts was an operation called couching (Blodi, 1996). This was a surgical procedure to displace the crystalline lens inside the eye which had become opacified, for varying reasons. The lens was usually pushed into the back of the eye and a person's vision was normally restored. This method of cataract treatment did not remove the lens from the eye, as with modern-day cataract extraction, but simply moved it into a place where it did not interfere with light hitting the retina, thereby allowing some restoration of vision. Couching itself was normally performed without anaesthetic and, according to Zegers (2005, p. 1429), in the 18th century patients were seated in an upright chair and held tightly by an assistant while the procedure was being performed.

Bach's treatment was performed by the travelling English eye surgeon, John Taylor (1703-1772). Although he had received training at St. Thomas' Hospital in London, he was "an oculist of note and notoriety" (Wade, 2008, p. 969). This was because he wrote detailed books about the eye whilst simultaneously causing a great deal of distress to his patients where his extremely expensive couching operations caused pain and also failed (Wade, 2008; Zegers, 2005). Indeed, he travelled throughout Europe performing these operations and instructed the patients that they were not to remove their bandages for a minimum of five days, by which time he had moved on to "the next town to operate on new victims" (Zegers, p. 1429). Zegers also reports that Taylor was right-handed and as such preferred to operate on the left eye, whether the patient needed it or not. His habit of covering the eye with bandages was also criticized because it increased the risk of post-operative infection. According to Tarkkanen (2013), "The Mayor of Leipzig had been asked for measures in case Bach would become unable to take care of his duties. After persuasion of his friends, Bach had both eyes operated by a travelling British eye 'surgeon' John Taylor" (p. 191).

Bach's first operation took place in Leipzig in March 1750. It was likely to have been Taylor's standard procedure to remove the cataract by couching. About one week later, Bach needed further surgery on that eye because the couching was followed by "anterior displacement of the lens, pupillary block and glaucoma" (Zegers, 2005, p. 1429). It must be remembered that this surgery took place in the pre-antiseptic era and many post-operative complications could have occurred as a result. Taylor decided to treat Bach with "bloodletting, laxatives and eye-drops of blood from slaughtered pigeons, pulverized sugar, or baked salt" (Zegers, p. 1429).

The newspaper *Vossische Zeitung* (1750, No. 4) stated that Bach's vision improved after the first operation; this would give some credence to the hypothesis that the cataract was successfully displaced. However, Taylor had significant influence with the newspapers of the time, because of the money he spent advertising his arrival in the towns that he visited, hence Zegers (2005) feels that this information is unreliable. He further dismisses Forkel's assertion that his eyes were painful before his surgery on the basis that his biography was written over a half a century after Bach's death and neither myopia nor cataract, on their own, are painful conditions. According to Tarkkanen (2013), Bach was extremely ill after the second procedure, suffering severe pain in his eyes and body; he was unable to play the organ and, indeed, was bedridden. It was at this point that Taylor "moved on and disappeared from Leipzig" (p. 192).

If Taylor operated on Bach's left eye first, as was his normal practice, and Bach had very little sight in his right eye, then if the first operation failed and on the second occasion he operated on the right, it is possible that "Taylor's interventions are compatible with most of the post-operative complications" (Zegers, 2005, p. 1430) described by his biographers. Hence Bach was left with very little sight and possibly died, according to Tarkkanen (2013), from "secondary phacoanaphylactic endophthalmitis" the following July (p. 191).

3. Forensic Literature Review

In the forensic handwriting examination literature, several features have been reported as characteristic of handwriting distortion caused by visual impairment. Features of handwriting written by those who are blind or visually-impaired reported by Beacom (1967) include: handprinting of the signature, poor alignment, preference for uppercase letters, square-shaped "r" forms, problems writing certain letters (e.g., j, b, d, k, h, f as the retraced movement of these letters creates difficulty for blind writers), difficulties with the letters "t" and "i" due to the

cross and dot formations in those letters, problems forming connectives between letters, lack of uniformity in size, illegibility, and incomplete signatures.

Lindblom (1983) reports that handwriting features associated with visual impairment include tremor, pen scratches, misalignment of words/letters, writing across or through other material, squared letters, overlapping of letters, ink errors, problems in writing certain letters, infrequent pen lifts, absence of “t” bars and “i” dots, inconsistent spacing, stunted letter designs, and flattened letter bases (due to use of visual aids).

In a forensic case study, Masson (1988) found that the handwriting was difficult to decipher because handwritten letters and words were written on top of another. Some of the primary effects of handwriting distortion included lack of baseline alignment, overwriting, entanglement, inconsistency in word and letter spacing, and erratic proportional relationships.

Komal et al. (1999) performed a statistical analysis of the writings of over 60 individuals who were blind and visually-impaired. The results showed that the writers exhibited overlapping/intermingling letters, unusual/distorted letter forms, ink failures (because the subjects could not see that the pen was not working), problems with certain letters (S, A, G, P, H, K), tremor, preference for capital letters, line quality problems, alignment, and inconsistent size.

4. Analysis

Three signatures dated in the late 1740s, which are attributed to J. S. Bach (Kobayashi, 1989; Pierpont Morgan Library, 1970) are the subject of question in this study as they are written during a time period when his vision is reported to have significantly deteriorated (reproduced in Figures 1, 2, and 3).

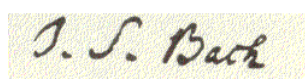


Figure 1. 1747

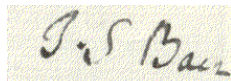


Figure 2. 1748



Figure 3. 1748

Table 1 summarizes the handwriting features associated with visual impairment from the four studies previously cited and discussed (Beacom (1967); Lindblom (1983); Masson (1988); and Komal et al. (1999)). In comparing the typical features of handwriting executed by those who are blind or have visual impairment to the Bach signatures in Figures 1, 2, and 3, there is limited support for the theory that someone who is blind (or severely visually impaired) wrote the Bach signatures in the 1740s. As reported in Table 1, some indices of visual impairment are observed in Figure 2, but the illegibility observed at the end of the signature could be caused by poor copy quality.

Examples of signatures attributed to J. S. Bach prior to the 1740s were included in the analysis (Kobayashi, 1989). It was observed that there were some notable variations amongst Bach signatures, which is partially evidenced by the three signatures used for comparison to represent pre 1740s signatures (Figures 4, 5, 6). Little evidence of handwriting indices of visual impairment were observed in the pre 1740s signatures (see Table 1). A comparison of the 1740s signatures to the pre 1740s signatures shows a high degree of similarity between Figures 1 through 3 (post 1740) and Figure 5 (pre 1740). No signs of deterioration were evident in the 1740s signatures although they were more simplistic in style than Figures 5 and 6 (notably the uppercase B).

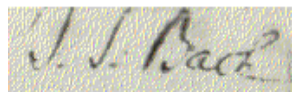


Figure 4. 1727/32

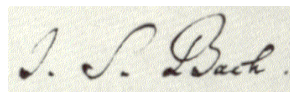


Figure 5. 1727/32



Figure 6. 1736

5. Discussion

Beacom (1967) reported that there can be a wide range of variation in handwriting performance by those who are blind. There can also be a difference between those who were blind at the time they learned to write in comparison to those who experienced severe visual impairment or blindness after they learned to write. J. S. Bach learned to write before he became severely visually impaired indicating that writing, such as his signature, would have been an overly-programmed skill in his motor memory. It was noted by Komal et al. (1999) that some subjects with partial visual impairment had “normal alignment, writing slant, writing pressure, line quality and connections” (p. 48). It was reported that J. S. Bach, as a youth, had strained vision and may have copied manuscripts with limited light (Zegers, 2005). He may have adopted visual strategies under such conditions and became accustomed to writing with dim light. There was no evidence among the signatures that Bach used signature aids or guides to assist with alignment of the signatures. It is not certain the level of severity of Bach’s visual impairment. However, if his vision was so poor that it required difficult and painful surgery, it is

reasonable to expect that his vision was impaired enough to affect his handwriting, especially since he was a composer and relied upon writing music as a primary source of income.

There is little to no evidence of visual impairment indices among the questioned Bach signatures from the late 1740s. The signatures were compared to earlier signatures and they were similar to at least one Bach signature from approximately 1730 (Figure 4). The lack of visual impairment indices in J. S. Bach's 1740s signatures lends some support to the theory postulated by Jarvis (2007) that more than one writer may have signed Bach's signatures and that another person may have signed on his behalf in the late 1740s.

Table 1		
<i>Handwriting Feature</i>	<i>Frequency in Bach signatures (late 1740s)</i>	<i>Frequency in Bach signatures (pre 1740s)</i>
Overwriting [2] [3]	None detected	None detected
Alignment [1] [2] [3] [4]	No internal alignment problems	No internal alignment problems
Entanglement, overlapping [2] [3] [4]	None detected	None detected
Inconsistent spacing [1] [2] [3]	Some compressed spacing in Figure 3	Some compressed spacing in Figure 6
Erratic proportions [3] [4]	None detected	None detected
Handprinting [1]	Fig. 3 has few disconnected, printed forms	None detected
Uppercase letters [1] [4]	No unusual uppercase letters	No unusual uppercase letters
Square-shaped letters [1] [2]	None detected	None
Difficulty writing letter forms [1][2][3]	None detected	None detected
Problems forming connectives between letters [1]	Some printed forms in Figure 3	None detected
Illegibility [1]	Figure 2 difficult to decipher at the end (probably due to poor quality copy)	None detected
Incomplete signatures [1]	Fully formed signature written with first and middle initials (typical of time period). Missing period after uppercase S (Fig. 2).	Fully formed signature written with first and middle initials (typical of time period)
Tremor [2] [4]	None detected	None detected
Pen scratches [2]	Possible scratches in Fig. 2 but may be due to poor quality copy	None detected
Ink errors/failures [2] [3]	None detected (possible in Fig. 2)	None detected
Infrequent pen lifts [2]	Consistent pen lifts	Consistent pen lifts
Stunted letter designs [2]	None detected	None detected
Flattened letter bases [2]	None detected	None detected
Distorted letter forms [3]	None detected	None detected
Line quality problems [4]	None detected	None detected

[1] Beacom (1967); [2] Lindblom (1983), [3] Masson (1988), and [4] Komal et al. (1999)

References

- Beacom, M. (1967). Handwriting by the blind. *Journal of Forensic Sciences*, 12(1), 37-59.
- Blodi, F. C. (1996). Cataract surgery. *The History of Ophthalmology*. Oxford: Blackwell Science, 165-75.
- David, H. T., Mendel, A., & Wolff, C. (1999). *The New Bach Reader [The Obituary]*. W. W. Norton & Co.
- EWB (Encyclopedia of World Biography). (2015). Johann Sebastian Bach Biography. Retrieved from: <http://www.notablebiographies.com/Ba-Be/Bach-Johann-Sebastian.html>
- Forkel, J. N. & Terry, C. S. (1920). *Johann Sebastian Bach: His life, art and work*. NY: Harcourt, Brace & Howe
- Foster, P. J., & Jiang, Y. (2014). Epidemiology of myopia. *Eye*, 28(2), 202-208.
- Gramophone. (2015). Johann Sebastian Bach (1685-1750): A Biography. Retrieved from: <http://www.gramophone.co.uk/editorial/johann-sebastian-bach-1685-1750-a-biography>
- Ho, D. (2010). Did Johann Sebastian Bach die from eye surgery complications? *Interlude*. Retrieved from: <http://www.interlude.hk/front/did-johann-sebastian-bach-die-from-eye-surgery-complications/>
- Jarvis, M. W. B. (2007). Did Johann Sebastian Bach write the six cello suites? (Doctoral thesis). Charles Darwin University.
- Kobayashi, Y. (1989). Die Notenschrift Johann Sebastian Bach's Dokumentation ihrer Entwicklung. *NBA*, 9(2). Kassel u.a.: Bärenreiter.
- Komal, S., Jasuja, O. P., Singla, A. K., & Singh, S. (1999). A study of the handwriting of visually impaired persons. *International Journal of Forensic Document Examiners*, 5, 39-53.
- Lindblom, B. (1983). Identifying characteristics in the handwriting of the visually impaired. *Canadian Society of Forensic Science Journal*, 16(4), 174-191.
- Masson, J. (1988). Deciphering the handwriting of the recently blinded. *Forensic Science International*, 38, 161-71.
- Mosby's Medical Dictionary. (2009). 8th ed., Elsevier. Farlex: The Free Dictionary: Refractive Error Retrieved from: <http://medical-dictionary.thefreedictionary.com/refractive-error>
- Nash, E. (2013). Cataracts. *InnovAiT*, 6(9), 555-562.
- NHS. (2015). Age-related cataracts. Retrieved from: <http://www.nhs.uk/Conditions/Cataracts-age-related/Pages/Introduction.aspx>
- NNDB. (2014). Johann Sebastian Bach. Retrieved from: <http://www.nndb.com/people/520/000059343/>
- Pierpont Morgan Library, NY. (1970). 'Wine & Taxes' letter of 1748 purportedly written by Johann Sebastian Bach.
- Tarkkanen, A. (2013). Blindness of Johann Sebastian Bach. *Acta ophthalmologica*, 91(2), 191-192.
- Wade, N.J. (2008). Chevalier John Taylor, ophthalmiater. *Perception*, 37, 969-72.
- Zegers, R. H. (2005). The eyes of Johann Sebastian Bach. *Archives of Ophthalmology*, 123(10), 1427-30.

Training- and Segmentation-Free Intuitive Writer Identification with Task-Adapted Interest Points

Angelika GARZ^a, Marcel WÜRSCH^a and Rolf INGOLD^a

^a *University of Fribourg, DIVA
1700 Fribourg; Switzerland*

[angelika.garz, marcel.wuersch, rolf.ingold]@unifr.ch

Abstract. Identifying the writer of a document establishes its authenticity or authorship and has several applications, notably in forensic and historical document analysis. Previous research has shown the potential of Interest Points (IP) for writer identification, but existing methods require segmentation or training. This paper evaluates the performance of intuitive features computed directly from IP properties rather than extracting descriptors at their locations; allowing for a training-free approach. Secondly, we show that adapting detectors to the specific task of writer identification is not only vital for performance but also allows for segmentation-free approaches. Experiments on widely-used datasets show the potential of the method applied self-contained and when combined with existing methods. Limitations of our method relate to the amount of data needed in order to obtain reliable models.

1. Introduction

Applications of Writer Identification (WI) are manifold. In handwriting recognition writer-dependent models tailored to the personal writing style allow for improved performance. Knowing a historical manuscript's scribe, its history, origin, and authenticity can be determined. In forensic investigations concerning fraud, homicide, suicide, or the execution of a last will, establishing the genuineness of a document is a task that often arises.

Current research in WI focuses on two problems: improving identification performance especially on large datasets (Louloudis et al., 2013), on the one hand; and explainability of system results, i.e., rendering the decision-making comprehensible to a human (Niels & Vuurpijl, 2005), on the other hand. Drawbacks of existing methods are the need for binarization or segmentation; open problems themselves (Pratikakis et al., 2013). IP-based methods offer the potential of circumventing the aforementioned drawbacks. Such methods detect salient points in handwriting in order to compute a descriptor at their locations. Using a so-called codebook of clustered descriptors from an independent training set, a probability distribution of descriptors is computed to characterize a writer. Literature focused on using various codebook clustering methods (Fiel & Sablatnig, 2012), or developing different descriptors and combinations (Jain & Doermann, 2014). A recent approach combines a codebook of IP descriptors and a histogram of scales and orientations computed from IP (Wu et al., 2014). For comprehensive reviews of WI methods relate to (M. Awaida, 2012; Schomaker, 2007; Sreeraj & Idicula, 2011).

In existing work great focus has been laid on the development of highly performant descriptors; however, parameters and properties of IP detectors themselves have not been regarded. This leads to potentially losing out on discriminant features due to both, IP not detected and disregarding information encoded in IP themselves. This paper addresses these two points. We directly compute features of IP properties rather than extracting descriptors and building a codebook; proposing a method that can be applied out of the box, and omitting a training phase. Our method is intuitive to understand for a human expert on the one hand, and fast to compute and performant on the other. We emphasize the importance of adapting an IP detector to the requirements of WI showing that it leads to improved results and moreover can render segmentation and binarization superfluous.

The remainder of this paper is structured as follows. Section 2 analyzes the features, followed by a description of the feature computation in Section 3. Results achieved and a comparison to existing work are given in Section 4, followed by a conclusion and outlook into future work.

2. The Scale - Dominant Orientation Histogram (SDO)

IP are defined as locations in an image with a two-dimensional signal change (Tuytelaars & Mikolajczyk, 2008); i.e., they are located at image structures such as corners, junctions, circles, or dots. We use an IP's dominant orientation, which describes the prevailing direction of gradients in its neighborhood, together with its spatial extent (scale) to compute a 2D histogram. An illustration of IP and their scales is shown in Figure 1 (the image is cropped for illustrative purposes - we extract IP from entire pages). While other IP detectors can be employed, as a proof of concept we chose the widely-used Difference-of-Gaussian (DoG) detector (Lowe, 2004).

Orientation and scale being properties intuitively understood, our feature allows for translation of the results comprehensible to human experts in document examination. A conceivable visualization that can be used as *visual fingerprint* of a handwriting sample is shown in Figure 2; and the information encoded in the features is summarized in the following. The slant is encoded as peaks across scales in the histogram. However, note that the dominant orientation captures several properties of the script; thus, the peaks might be deviated from the overall slant (Figure 2 d). Furthermore, the distribution of stroke orientations along with their scales allows for deducing character shapes, e.g. roundness, especially of loops and holes; and uniformity of the handwriting, i.e., how parallel the strokes are, or consistent the handwriting is. While round characters produce a higher variance in stroke orientations



Figure 1 Cropped example of a text line with the detected IP and their dominant orientations denoted as circles, where the size indicates the scale, and the line originating from the center the dominant orientation. Several orientations indicate multiple IP with different dominant orientations at the same location.

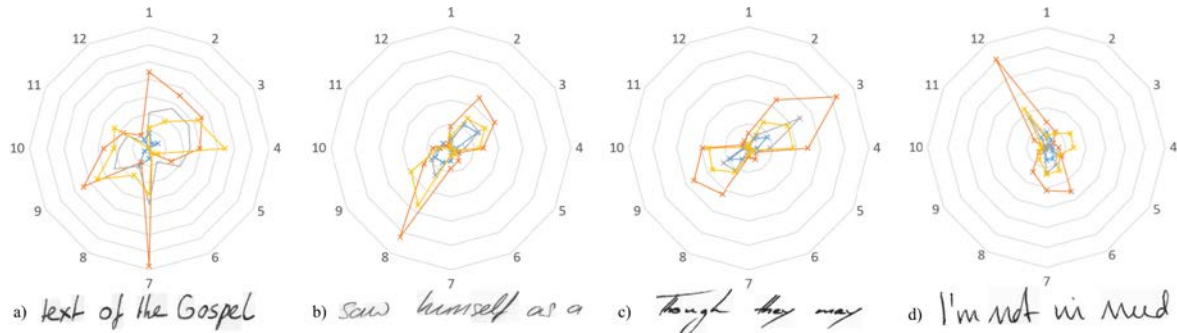


Figure 2 Samples (cropped for legibility) and their features as polar histogram. Angular coordinates denote quantized orientations, radial coordinates denote proportional frequency, and scales are denoted by color-coded markers. For legibility the 4 smallest scales only are shown and markers are connected. Round uniform writing causes high (a), long slanted strokes are reflected in two opposing distinct peaks (c), and angular writing one distinct peak (b, d).

(Figure 2 a), elongated narrow characters with angular shapes induce clear peaks in the orientation histogram (Figure 2 b, d). Furthermore, compact condensed writing has smaller structures compared to loose or uncondensed writing; thus producing a higher relative number of small IP. Continuous writing with long strokes generates a signature of small IPs different to one of intermittent writing produced by, e.g., little pressure put on the pen.

Scales of IPs are not discriminant enough by themselves but provide subsidiary cue when combined with other properties. Small-scale IP cover the width of a stroke, allowing for inference of information about, e.g., stroke widths including their variance. Large scales represent big loops of characters, or spaces between ascenders, descenders, characters, words, or lines.

A formal translation of the histogram into a verbal description as well as an interactive visualization an expert can use to explore aspects of the visual fingerprint described are beyond the scope of this paper.

(Wu et al., 2014) also propose a scale and orientation histogram, yet their method requires prior word segmentation. Since segmentation of text lines and words is an open research topic (Stamatopoulos et al., 2013) and potentially introduces errors in further processing, we omit it in our approach.

3. Feature extraction

As feature we compute the normalized probability density function of a 2D histogram size $X \times Y$, with X and Y being the total number of quantized scales and dominant orientations, respectively. Quantization inherently has an effect on the information captured (between-writer variability) and the invariance incorporated (within-writer variability). Using DoG, we decompose an image into a scale space¹ of $X = M \times N$, with M octaves and N sub-levels. IP are then identified as local extrema of the scale space, i.e., a pixel is selected as IP if it is the minimum or maximum compared to its eight neighbors at the same scale and nine corresponding neighbors in the adjacent scales, and its magnitude exceeds the threshold th . The scale s_i of IP i is in the range $1 \leq s_i \leq M \times N \times \sigma \times m_i$, where σ is the standard deviation of the Gaussian kernel for creating the scale space, and m_i is the magnitude of the extrema. It is quantized using step size σ , which groups IP according to their location in the scale space. The dominant orientation is quantized from $[0^\circ, 360^\circ]$ with angle step α .

The best parameter combination for the DoG detector was determined on the *ICDAR2011 cropped dataset* (Louloudis et al., 2011) as $[M = 3, N = 6, \sigma = 1.3, th = 5, r = 0]$ with th being the detector sensitivity, and r the edge threshold, where 0 means that IP located at edges are not suppressed. With an angle step $\alpha = 30$ we create a feature vector of size 216 which we truncate to the first 108 elements (smallest scales) based on experiments. Note that changing the size of the scale space X and truncating are not the same operation since the actual scale of an IP additionally depends on the strength of extrema the IP is located at.

4. Evaluation

Performance Evaluation. We conducted our experimental study on full pages of the datasets listed in Table 1. The evaluation design follows the *ICDAR2011 competition* evaluation procedure, except that only the TOP-1 identification criterion is reported, i.e., the document ranked first has to be by the same writer as the query. We employ a naïve nearest neighbor approach in a leave-one-out manner for identification, and the χ^2 distance metric as dissimilarity measure between two documents. Significance is tested using a χ^2 -Test ($p < 0.05$).

Table 1 Overview of the datasets used

Dataset	# writers	# pages	# lines	Language
IAM ² (Marti & Bunke, 2002)	657	2	3-14	English
ICDAR2013 (Louloudis et al., 2013)	250	4	4	English, Greek
ICDAR2011 full (Louloudis et al., 2011)	26	8	13-23	English, French, German, Greek
ICDAR2011 cropped	26	8	2	English, French, German, Greek

Table 2 Comparison of state-of-the-art methods (a, b) and our proposals (c-e) on the test datasets.

Method	IAM	ICDAR2013	ICDAR2011 full	ICDAR2011 cropped
(a) (Wu et al., 2014)	98.5	94.8	99.5	95.2
(b) (Jain & Doermann, 2014)	94.7	N/A	N/A	N/A
(c) SDO-E T	81.9	81.4	98.6	87.5
(d) Descriptor (Fiel & Sablatnig, 2012)	82.3	80.1	99.5	80.8
(e) SDO-E T & Descriptor	86.9	87.3	98.6	88.0

Table 3 Evaluation of IP detector parameters on the *IAM* dataset. SDO is our proposal, with postfix “-E” for IP on edges permitted and “-NS” for IP on background suppressed. F is the full feature vector (size 216), T the vector truncated to 108.

Method	Settings	Result	
(1) (Wu et al., 2014) Documents	Scale Orientation Histogram on full pages [$M = 6, N = 3$]	64.0	
(2) (Wu et al., 2014) Words	Scale Orientation Histogram on segmented words [$M = 6, N = 3$]	78.4	
(3) Our implementation of (1) ³	[$M = 6, N = 3, r = 0.1$]	65.5	
		F	T
(4) SDO	[$M = 3, N = 6, r = 0.1$]	79.1	79.6
(5) SDO-E	[$M = 3, N = 6, r = 0$]	81.3	81.9
(6) SDO-E-NS	[$M = 3, N = 6, r = 0$], no background IP	79.8	80.6
(7) SDO-NS	[$M = 3, N = 6, r = 0.1$], no background IP	75.3	76.3
(8) SDO (Words)		65.2	

Results are summarized in Table 2. Our method (c) achieves competitive scores on the ICDAR2011 full dataset. The performance declines when having considerably less data: ICDAR2011 cropped only contains two text lines per page. Note that the performance difference between (a) and (c) on the ICDAR2011 sets is insignificant. In order to assess potential gains of feature combination, we additionally combined our method with a descriptor-codebook-based approach (d), which is our own implementation of (Fiel & Sablatnig, 2012)⁴. The codebook is computed on an independent dataset. On larger datasets such as *IAM* and *ICDAR2013*, feature combination (e) significantly boosts the performance, showing that our feature captures complementary information.

Parameter Evaluation. In the following we show that appropriate parameters for IP detectors are critical for the overall performance of an IP-based method. IP originate from object detection and recognition, where a homography (mapping between two projections of an object) is computed that requires stable and repeatable IP. However, the task of writer identification is of different nature (we need to describe the strokes present), and unreflected adopting of standard parameters suitable for one task is likely to being ill-suited for another.

For the evaluation of the DoG detector’s parameters we used the IAM dataset for its size and variability in writing styles and amounts of data per page (3-14 lines). The TOP-1 identification results are shown in Table 3. With the settings reported in (Wu et al., 2014) as baseline (3), we tested our feature with following alterations: improved selection of scale space parameters [M, N] (4); permitting IP located on edges [r] (5), and excluding IP on the background (7), i.e., those IP corresponding to minima in the scale space, as means to avoid segmentation; and their combination (6). First and foremost, using the best combination (6) and optimizing the feature vector (5 T) we can forego segmentation with significant increase in performance with respect to (2). Furthermore, comparing 1 and 1, we see that IP located on white space do encode valuable information. We want to stress that IP located on edges capture supplementary information as they describe prominent strokes otherwise not detected, see 1 and 1, and particularly 1 and 1. For comparison, we show the result of the basic SDO (4) on the segmented text line images of the IAM dataset (8) Figure 3 illustrates the effect of the parameter combinations evaluated.

² The dataset has been modified to contain two samples per writer according to the procedure described in (Wu et al., 2014).

³ Lacking information about the original paper’s parameters, we use the parameter combination determined in Section 3.

⁴ Note that the performance reported on the *IAM* dataset (90.8) by the authors is not directly comparable to the literature since they used only a subset of documents for evaluation: writers with only one sample are not evaluated, and 2 to 58 reference samples are kept for identification, while for each writer we keep only one reference sample in our evaluation. It is inherent that fewer writers and more reference samples result in better performance. To assess whether our implementation (d) is comparable to the original, we evaluated it according to the strategy explained, achieving a slightly better identification rate of 92.4.

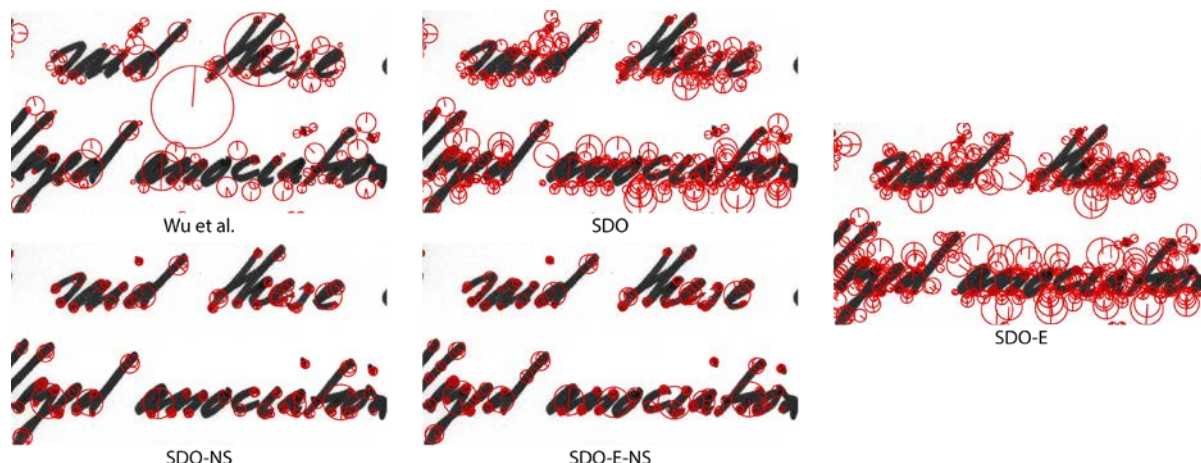


Figure 3 Visual examples of the effect of the parameter combinations chosen. Wu et al. is shown in the top-left corner. The best-performing parameter combination (SDO-E) is shown in the third column (refer to Table 3 for the exact parameters).

5. Conclusion

The writer identification method presented in this paper makes use of overlooked properties of IP as feature, rather than employing a codebook of descriptors as in existing methods. Our method is segmentation-free and does not require training, as we compute the feature directly as a 2D histogram of interest points' scales and dominant orientations. An additional contribution targets the need of careful adaption of methods originating from another field. We showed that adapting the detector to the task of writer identification, on the one hand, boosts performance since IP capturing additional information about a writer are detected, and facilitates a segmentation-free approach, on the other.

Opposing the inference of (Wu et al., 2014), who state that word segmentation is essential – for IP in inter-word and inter-line space being instable – we conclude that spaces encode valuable additional information and boost performance, rendering segmentation unnecessary. Our feature outperforms their proposition by a significant margin. Furthermore, we showed that using IP detected on the foreground only, are another alternative to word segmentation with the limitation of losing some performance with respect to a method including inter-space IP.

One limitation of the features proposed is the amount of data needed to create a reliable model of a writer; however, combined with a descriptor-based method performance can be boosted with respect to both features, especially for large datasets. We propose to incorporate our features into future IP-based methods for its simplicity, capability to capture complementary information, good performance, and minor expense to compute.

References

- Fiel, S., & Sablatnig, R. (2012). Writer Retrieval and Writer Identification Using Local Features. In *Int. Wksp on Document Analysis Systems* (pp. 145–149).
- Jain, R., & Doermann, D. (2014). Combining Local Features for Offline Writer Identification. In *Int. Conf. on Frontiers in Handwriting Recognition* (pp. 583–588).
- Louloudis, G., Gatos, B., Stamatopoulos, N., & Papandreou, A. (2013). ICDAR 2013 Competition on Writer Identification. In *Int. Conf. on Document Analysis & Recognition* (pp. 1397–1401).
- Louloudis, G., Stamatopoulos, N., & Gatos, B. (2011). ICDAR 2011 Writer Identification Contest. In *Int. Conf. on Document Analysis & Recognition* (pp. 1475–1479).
- Lowe, D. G. (2004). Distinctive Image Features from Scale-Invariant Keypoints. *Int. J. of Computer Vision*, 60(2), 91–110.
- M. Awaida, S. (2012). State of the Art in Off-line Writer Identification of Handwritten Text and Survey of Writer Identification of Arabic Text. *Educational Research and Reviews*, 7(20).
- Marti, U., & Bunke, H. (2002). The IAM-Database: An English Sentence Database for Offline Handwriting Recognition. *Int. J. on Document Analysis & Recognition*, 5(1), 39–46.
- Niels, R., & Vuurpijl, L. (2005). Using Dynamic Time Warping for Intuitive Handwriting Recognition. *Int. Graphonomics Soc.*, 217–221.
- Pratikakis, I., Gatos, B., & Ntirogiannis, K. (2013). ICDAR 2013 Document Image Binarization Contest (DIBCO 2013). In *Int. Conf. on Document Analysis & Recognition* (pp. 1471–1476).
- Schomaker, L. (2007). Advances in Writer Identification and Verification. In *Int. Conf. Document Analysis & Recognition* (pp. 1268–1273).
- Sreeraj, M., & Idicula, S. M. (2011). A Survey on Writer Identification Schemes. *Int. Journal of Computer Applications*, 26(2), 23–33.
- Stamatopoulos, N., Gatos, B., Louloudis, G., Pal, U., & Alaei, A. (2013). ICDAR 2013 Handwriting Segmentation Contest. In *Int. Conf. on Document Analysis & Recognition* (pp. 1402–1406).
- Tuytelaars, T., & Mikolajczyk, K. (2008). Local Invariant Feature Detectors: A Survey. *Foundation and Trends in Computer Graphics and Vision*, 3(3), 177–280.
- Wu, X., Tang, Y., & Bu, W. (2014). Offline Text-Independent Writer Identification Based on Scale Invariant Feature Transform. *IEEE Trans. on Information Forensics and Security*, 9(3), 526–536.

Acknowledgement. This work has been supported by the Swiss National Science Foundation project 205120_150173.

A Survey of Forensic Handwriting Examination Research in Response to the NAS Report

Heidi H. HARRALSON ^a, Elizabeth WAITES ^b and Emily J. WILL ^c

^a East Tennessee State University, Johnson City, Tennessee, USA

^b Nashville, Tennessee, USA

^c Raleigh, North Carolina, USA

^aspectrum008@aol.com, ^bwaiteslaw@gmail.com, ^cewill@Qdewill.com

Abstract. Advances in technology and scientific development in forensic handwriting examination (FHE) require a review in response to the challenges published in the NAS Report. This survey summarizes the advances made in theoretical and methodological approaches to handwriting examination including a review of research on the proficiency of FHEs. Technology has impacted FHE including analysis of e-signatures and use of technology for signature and handwriting authentication. A review of legal cases in the U.S. confirms how research and technological advances have met legal challenges and impacted decisions in the courtroom.

1. Introduction

In 2009, the NAS Report challenged the forensic sciences in several areas including forensic handwriting examination (FHE). Specifically, the NAS Report stated that the “scientific basis for handwriting comparisons needs to be strengthened. . .there has been only limited research to quantify the reliability and replicability of the practices used by trained document examiners” (p. 5-30). In the report there was discussion about the variability of handwriting. To determine if those challenges have been addressed by recent research, a literature review of FHE research for the time period 2009-2014 was conducted using Google Scholar, journal databases, and specific journals pertaining to forensic science. Publication information was extracted and organized according to subject themes that are relevant to FHE. A comprehensive review of the state of the art in FHE over the past 10 years will be published separately. This paper is a condensed survey of FHE research in response to the NAS Report and a review of U.S. legal decisions related to FHE challenges.

2. Handwriting Examination: Theory, Proficiency, and Methods

1. Theory. Definition of a complexity theory for handwriting began in 1996 with publications of the work of Drs. Bryan Found and Doug Rogers, then at LaTrobe University in Australia. There has been work on this topic since 2009 by Alewijnse et al. (2011) and Pepe et al. (2012). Continued refinement of the complexity theory supports scientific methodology in the evaluation and comparison of handwriting.

2. Proficiency. Several studies discuss the expertise of FHEs and proficiency testing, all related to the identification of handwriting authorship. Proficiency in evaluating disguised and simulated signatures and/or handwriting was researched by Bird et al. (2010, 2011, 2012) and Al-Musa et al. (2010). Guest et al. (2011) studied the inferences made by FHEs regarding handwriting dynamics as indicators of accuracy. The nature of FHEs authorship opinions was evaluated over a five year period of blind validation trials (Found & Rogers, 2008). Dewhurst et al. (2014) looked at the effects of motivation on the behavior of lay subjects when participating in handwriting trials. Holmes et al. (2011) discussed the use of online proficiency testing, as compared to more traditional methods of testing. The research in this area continues to inform us as to the proficiency of FHEs and helps to target problematic areas that can be corrected by training and testing.

3. Handwriting Features and Variability. There is a considerable body of recent research on handwriting features and variability which increases the information we have concerning inter-writer and intra-writer variability and handwriting individuality lending support for the scientific basis of handwriting comparison.

Research was found on handwriting features of special populations representing languages, special groups, etc. (Durina, 2009; Haddad et al., 2009; Turnbull et al., 2010; Al-Musa & Platt, 2011; Savoie, 2011; Al-Hadhrani et al., 2014). Factors influencing handwriting included studies on writing position and conditions (Equey et al., 2007; Sciacca et al., 2011). A study on handedness, age, and gender was carried out by Hayes et al. (2009). Simsons et al. (2011) studied the effects of spatially constraining signatures. Studies associated with simulation and disguise were carried out in order to understand processes and obtain handwriting feature predictors (Al-Musa et al., 2013; Al-Musa & Platt, 2011; Cadola et al., 2013; Bird et al., 2013; Mohammed et al., 2014; Caligiuri et al., 2012). Specific features were researched including evaluation of letter shapes (Marquis et al., 2011) and inferring speed from writing (Will, 2012). The handwriting variability associated with electronic signatures and the dynamic features that can be examined from them was reviewed by Flynn (2012) and Nicolaidis (2012). A methodology for electronic signature examination was developed by Harralson (2013).

The influence of health on handwriting production is another handwriting variable that has received considerable research attention. Cognitive impairment, dementia, mental and developmental disorders and their

effects on handwriting were researched by Balistrino et al. (2012), Caligiuri et al. (2014), Prunty et al. (2014), and Schwid & Teulings (2013). Kinematic studies examined handwriting features associated with healthy adults, movement disorders, and forgery (Harralson et al., 2008; Caligiuri & Mohammed, 2012; Caligiuri et al., 2014). Sadreddin (2013) reviewed the impact of DBS on daily motor activities, including handwriting.

4. Replicability and Reliability. In quantifying the replicability and reliability of handwriting, there has been research into the application of likelihood ratios in handwriting examination. Specifically, Marquis et al. (2011) applied multivariate likelihood ratios to evaluation of the shape of handwritten characters and studied the Bayes factor of assessment of handwriting features. Davis et al. (2011) studied subsampling to estimate the strength of handwriting evidence. Application of likelihood ratios for handwriting evidence was studied by Marquis et al. (2011), Hepler et al. (2012), and Taroni et al. (2012; 2014). In critiquing the reliability of FHEs in the application of methods, Reinoud et al. (2013) discussed procedural changes needed to counter bias among FHEs and Found & Ganas (2013) studied the management of domain irrelevant context information in FHE casework.

3. Handwriting Examination Technology

Extensive published research exists on developments in signature verification which supports research into the replicability and reliability of handwriting. A survey of computer methods in FDE was previously explored by Srihari & Leedham (2003). Automated handwriting examination systems such as FISH and WANDA (Franke et al., 2004) and CEDAR-FOX (Srihari et al., 2005, 2007; Owen, 2013) rely on handwriting databases, enable automated examination features, and produce statistical analyses. FISH and WANDA were designed to help automate the handwriting examination process and increase efficiency through the computerized ability to scan, digitize, measure, store, and compare handwriting samples. Automatic feature extraction is based on the premise that it is the combination of unique characteristics that establishes handwriting identification; one feature alone is not sufficient to establish identification. The FBI, through the coordinated efforts of scientists and computer engineers, developed the Forensic Language-Independent Automated System for Handwriting Identification (FLASH-ID) (Sciometrics, LLC, 2014). Although not meant to replace FHEs, computerized methods of analysis aid in establishing statistical support for forensic opinions.

Research using computational methods to quantify the individuality of handwriting has been explored more recently by Saunders et al. (2011). The role of automation in handwriting examination was discussed and illustrated through a case study by Srihari & Singer (2014) in a way that synthesizes the role of the human expert with the computational ability that automation provides in offering statistical analysis. Essentially, automating some of the work carried out by human examiners offers efficiency in case load especially when there is a large volume of documents requiring analysis. Automation also operationalizes the process providing efficiency, reliability, and standardization in forensics. Other studies involving automation included Liwicki (2012), Parodi et al. (2014), Parziale et al. (2014), and Putz-Leszczynska (2012, 2014) who studied various aspects of online verification. Malik et al. (2014) compared the signature verification performance of humans versus machines.

Experimental eye-tracking is a technologically novel way to learn about FHE cognition. An eye-tracking study found that FHEs spend more time examining model signatures than forged signatures, and that genuine signatures with a higher degree of complexity also had longer observation times than signatures with low complexity (Pepe et al., 2012). These studies may have future relevance in developing technology that can be linked to the computer in evaluating handwriting, especially in programming software that evaluates handwriting similar to the way a human examiner evaluates handwriting.

4. Legal Review

Recent court decisions continue to interpret the *Daubert* requirement of reliability in assessing new scientific and technological developments. Standardized methods developed by independent laboratories continue to confer legitimacy when used to develop new technologies (*City of Pomona*, 2014). Thus, the traditional “battle of the experts” is an element given to the weight of evidence by a jury, and should not be excluded pre-trial by the judicial officer. The existence of scholastic disagreement is an appropriate courtroom debate, and was the reason why opponent’s argument of a relatively small a reference database in *Pomona* was insufficient objection for the Court to question technological reliability solely based unknowns in the potential rate of error. Pre-trial challenges to expert testimony are overcome when the testimony is shown to be reliable and helpful to the jury, not “whether the expert is right or wrong” (*City of Pomona*, p. 13).

Where technology is “novel and untested,” case law has affirmed the exclusion of evidence (*Tyson*, 2009). The exception appears to be government investigative software, as courts are hesitant to permit public disclosure (*Chiardio*, 1st Cir. 2012). FBI investigative innovations were excused from peer review (*Chiardio*, p. 278). Similarly, selective application of some, but not all, potential factors into a structured analysis amounts to a “disagreement over, not an absence of, controlling standards [and] is not a basis to exclude expert testimony” (*Pomona*; see also *Tampa Bay*, 11th Cir., 2013). The District of Columbia Court of Appeals has similarly

reasoned that “scientists significant either in number or experience must publicly oppose a new technique or method as unreliable before the technique or method does not pass muster under *Frye*” (Pettus, 2012).

The *Herrera* opinion, penned by the learned Judge Posner, provides that handwriting expert evidence “doesn’t have to be infallible to be probative” (Herrera, 7th Cir., 2013). Also from the Seventh Circuit: “Law must apply itself to the life of a society driven more and more by technology and technology improvements” (Lapsley, 2012). The courts have previously recognized that “experience is the predominant, if not sole, basis for a great deal of reliable expert testimony” (Jones, 6th Cir., 1997; see also 2000 Advisory Comment to Fed. R. Evid. 702). The use of cutting edge tools in conjunction with an expert’s independent confirmation of system accuracy is therefore generally admissible evidence to support the expert’s testimony and ultimate professional opinion.

5. Conclusion

A review of the research published over the past few years clearly shows that there has been a response to the challenges presented in the NAS Report. Prior research established that FHEs are more skilled than laypersons. However, recent research is instructing us as to the limitations that FHEs demonstrate concerning problematic areas and where further training and testing is required. Published research shows that FHEs are addressing concerns regarding handwriting variability, reliability, and replicability. Methods have been refined that incorporate advancing technology and research. A legal challenge to use of handwriting evidence in the courtroom, based on criticism from the NAS Report, was successfully defended (Pettus, 2012). While continued research work is necessary in all forensic disciplines, especially in the face of technological advances, published research since 2009 clearly shows that the scientific basis for handwriting comparison is being addressed through research, application of advanced technology, improved methods, and in the successful rebuttal of legal challenges.

References

- Alewijnse, L.C., van den Heuvel, E.C., & Stoel, R.D. (2011). Analysis of signature complexity. *Journal of Forensic Document Examination*, 21, 37-49.
- Al-Hadhrani, A.N., Allen, M., Moffatt, C., & Jones, A.E. (2015). National characteristics and variation in Arabic handwriting. *Forensic Science International*, 247, 89-96.
- Al-Musa Alkahtani, A. (2010). The ability of forensic handwriting examiners to judge the quality of signature simulations in an unfamiliar writing system. *Journal of the American Society of Questioned Document Examiners*, 13(2), 65-69.
- Al-Musa Alkahtani, A., & Platt, A.W. (2011). A statistical study of the relative difficulty of freehand simulation of form, proportion, and line quality in Arabic signatures. *Journal of Forensic Sciences*, 56(4), 950-3.
- Al-Musa Alkahtani, A. (2013). Age-related statistical differences in the ability of Arabic writers to simulate elements in Arabic signatures. *Journal of Forensic Document Examination*, 23, 25-39.
- Balestrino, M., Fontana, P., Terzuoli, S., Volpe, S., & Inglese, M.L., Cocito, L., (2014). Altered handwriting suggests cognitive impairment and may be relevant to posthumous evaluation. *Journal of Forensic Sciences*, 57(5), 1252-8.
- Bird, C., Found, B., Ballantyne, K., & Rogers, D. (2010). Forensic handwriting examiners’ opinions on the process of production of disguised and simulated signatures. *Forensic Science International*, 195(1), 103-107.
- Bird, C., Found, B., & Rogers, D. (2010). Forensic document examiners’ skill in distinguishing between natural and disguised handwriting behaviors. *Journal of Forensic Sciences*, 55(5), 1291-1295.
- Bird, C., Stoel, R. D., Found, B., & Rogers, D. (2011). Skill characteristics of forensic handwriting examiners associated with simulated handwritten text. *Journal of the American Society of Questioned Document Examiners*, 14(2), 29-34.
- Bird, C., Found, B., & Rogers, D. (2012). Forensic handwriting examiners’ skill in detecting disguise behavior from handwritten text samples. *Journal of Forensic Document Examination*, 22, 15-23.
- Bird, C., Found, B., & Rogers, D. (2013). Predictors of disguised and simulated handwritten text. *Journal of the American Society of Questioned Document Examiners*, 16(2), 13-8.
- Cadola, L., Margot, P.A., & Marquis, R. (2013). Are simple signatures so easy to simulate? *Journal of the American Society of Questioned Document Examiners*, 16(2), 3-11.
- Caligiuri, M.P. (2013). Apraxic agraphia in patients with dementia. *Journal of Forensic Document Examination*, 23, 15-23.
- Caligiuri, M.P., et al., (2014). Kinematics of signature writing in healthy aging. *Journal of Forensic Sciences*, 59(4), 1020-4.
- Caligiuri, M.P., & Mohammed, L.A. (2012). *The Neuroscience of Handwriting*. Boca Raton, FL: CRC Press.
- Caligiuri, M.P., Mohammed, L.A., Found, B., & Rogers, D. (2012). Non-adherence to the isochrony principle in forged signatures. *Forensic Science International*, 223(1-3), 228-32.
- City of Pomona v. SQM North American Corp.*, No. 12-55147 (9th Cir. 2014).
- Daubert v. Merrill Dow Pharmaceuticals*, 509 U.S. 579, 113 S.Ct. 2786, 125 L.Ed.2d 469 (U.S.S.Ct. 1993).
- Davis, L.J., Saunders, C.P., Hepler, A., & Buscaglia, J. (2012). Using subsampling to estimate the strength of handwriting evidence via score-based likelihood ratios. *Forensic Science International*, 216 (1-3), 146-57.
- Dewhurst, T. N., Found, B., Ballantyne, K. N., & Rogers, D. (2014). The effects of extrinsic motivation on signature authorship opinions in forensic signature blind trials. *Forensic Science International*, 236, 127-132.
- Durina, M.E., Caligiuri, M.P. (2009). The determination of authorship from a homogenous group of writers. *Journal of ASQDE*, 12(2), 77.
- Equy, C., Marquis, R., Mazzella, W.D. (2007) Influence of writing position on the dimensions of signatures. *Journal of ASQDE*, 10, 53-9.
- Federal Rules of Evidence. Rule 702, Advisory Commission Comment from 2000.
- Fenoff, R. (2013). The Neuroscience of Handwriting. *Forensic Science International*, 229(1-3), 21-22.
- Flynn, W. J. (2012). Conducting an examination of electronically captured signatures. *Journal of ASQDE*, 15(1), 3-10.
- Found, B., & Rogers, D. (2008). The probative character of forensic handwriting examiners’ identification and elimination opinions on questioned signatures. *Forensic Science International*, 178(1), 54-60.
- Found, B., & Ganias, J. (2013). The management of domain irrelevant context information in FHE casework. *Science and Justice*, 53(2), 154.

- Franke, K., Schomaker, L., Veenhuis, C., Vuurpijl, L., van Erp, M., & Guyon, I. (2004). WANDA: A common ground for forensic handwriting examination and writer identification. *ENFHEX News*, 1(4), 23-47.
- Guest, R., Fairhurst, M., Abreu, M., & Linnell, T. (2011). Exploiting interface mechanisms in the assessment of forensic document examination methodologies for signatures. *Journal of Forensic Document Examination*, 21, 5-15
- Haddad, A.A., White, P.C., Cole, M.D. (2009). Examination of a collection of Arabic signatures. *Journal of ASQDE*, 12(1), 35-53.
- Harralson, H. H. (2013). *Developments in handwriting and signature identification in the digital age*. Waltham, MA: Anderson.
- Harralson, H. H., Teulings, H.-L., & Farley, B. (2008). Comparison of handwriting kinematics in movement disorders and forgery. *Journal of Forensic Document Examination*, 19, 41-52.
- Hayes, J.L. (2009). Influence of age, gender and handedness in signature imitation. *Journal of ASQDE*, 12(2) 91-9.
- Hepler, A.B., Saunders, C.P., Davis, L.J., & Buscaglia, J. (2012). Score-based likelihood ratios for handwriting evidence. *Forensic Science International*, 219(1-3), 129-40.
- Holmes, L., Ostrum, B., & Barton, A.J. (2011). Online proficiency testing for signature comparison by forensic document examiners and non-examiners. *Journal of the American Society of Questioned Document Examiners*, 14(1) 19-36.
- Lapsley v. Xtek, Inc.*, 689 F.3d 804, 811 (7th Cir. 2012).
- Liwicki, M. (2012). Automatic signature verification: in-depth investigation of novel features and different models. *Journal of Forensic Document Examination*, 22, 25-39.
- Malik, I.M., Liwicki, M., Dengel, A., & Found, B. (2014). Man vs. machine: A comparative analysis for signature verification. *Journal of Forensic Document Examination*, 24, 21-35.
- Marcelli, A., Rendina, M., & DeStefano, C. (2011). Disguising writer's identification. *Journal of Forensic Document Examination*, 21, 23.
- Marquis, R., Bozza, S., Schmittbuhl, M., & Taroni, F. (2011). Handwriting evidence evaluation based on the shape of characters: Application of multivariate likelihood ratios. *Journal of Forensic Sciences*, 56 (s1), S238-42.
- Marquis, R., Bozza, S., Schmittbuhl, M., & Taroni, F. (2011). Quantitative assessment of handwriting evidence: the value of the shape of the letter "a." *Journal of Forensic Document Examination*, 21, 17-22.
- Mohammed, L., Found, B., Caligiuri, M., & Rogers, D. (2014). Dynamic Characteristics of Signatures: Effects of Writer Style on Genuine and Simulated Signatures. *Journal of Forensic Science*, November 24, 2014.
- National Research Council. (2009). *Strengthening forensic science in the United States*. Washington, DC: National Academies Press.
- Nicolaides, K. N. (2012). Using acceleration/deceleration plots in forensic analysis of electronically captured signatures. *Journal of the American Society of Questioned Document Examiners*, 15(2), 29-43.
- Owen, J. (2014). Screening the handwriting of different individuals using CEDAR-FOX. *J. of Forensic Document Examination*, 2014, 53-66.
- Parodi, M., Gómez, J., Alewijnse, L., & Liwicki, M. (2014) Online signature verification: Automatic feature selection vs. FHE's choice. *Journal of Forensic Document Examination*, 24, 5-19.
- Parziale, A., et al. (2014). Modeling Stability in On-Line Signatures. *Journal of Forensic Document Examination*, 24, 37-46.
- Pepe, A.L., Rogers, D., & Sita, J. (2012). A consideration of signature complexity using simulators' gaze behaviour. *Journal of Forensic Document Examination*, 22, 5-13.
- Pettus v. United States*, 37 A.3d 213 (D.C. Cir. 2012).
- Prunty, M.M., Barnett, A.L., Wilmut, K., & Plumb, M.S. (2014). An examination of writing pauses in the handwriting of children with Developmental Coordination Disorder. *Research in Developmental Disabilities*, November, 2014, 35(11), 2894-905.
- Putz-Leszczynska, J., & Pacut, A., (2012). Model approach to DTW signature verification using error signals. *Journal of Forensic Document Examination*, 22, 41-54.
- Putz-Leszczynska, J., & Pacut, A., (2014). Modeling stability in on-line signatures. *Journal of Forensic Document Examination*, 24, 47-52.
- Sadreddin, A., (2013). Review of tremor: Impact on activities of daily living pre and post deep brain stimulation. *Journal of Forensic Document Examination*, 23, 5-13.
- Saunders, C. P., Davis, L. J., & Buscaglia, J. (2011). Using automated comparisons to quantify handwriting individuality. *Journal of Forensic Science*, 56(3), 683-9.
- Savoie, K. (2011). The frequency of occurrence of specific handwriting characteristics within a limited population. *Journal of the American Society of Questioned Document Examiners*, 14(2) 29-34.
- Schwid, B., & Tuelings, H. (2013). Writings of a person with dissociative identity disorder: A longitudinal and kinematic study. *Journal of Forensic Document Examination*, 23, 41-61.
- Sciacca, E., Langlois-Peters, M., Margot, P., & Velay, J. (2011) Effects of different postural conditions on handwriting variability. *Journal of Forensic Document Examination*, 21, 51-60.
- Sciacca, E., Langlois-Peters, M., Gilhodes, J., Margot, P., & Velay, J. (2011). The range of handwriting variability under different writing conditions. *Journal of Forensic Document Examination*, 19, 5-13.
- Sciometrics, LLC. (2014). Sciometrics Flash ID. Retrieved from: <http://sciometrics.com/products/sciometrics-flash-id.html>.
- Simons, D., Spencer, R.J., & Auer, S. (2011). The effects of constraining signatures. *Journal of ASQDE*, 14(1) 39-50.
- Srihari, S. N., Huang, C., & Srinivasan, H. (2005, January). Search engine for handwritten documents. In *Electronic Imaging 2005* (pp. 66-75). International Society for Optics and Photonics.
- Srihari, S. N., & Leedham, G. (2003). A survey of computer methods in forensic document examination. *Proceedings of IGS, Scottsdale*.
- Srihari, S. N., Srinivasan, H., & Kartik, D. (2007). Questioned Document Examination using CEDAR-FOX. *Journal of Forensic Document Examination*, 18, 1-19.
- Srihari, S. N., & Singer, K. (2014). Role of automation in the examination of handwritten items. *Pattern Recognition*, 47(3), 1083-1095
- Stoel, R.D., Dror, I.E., & Miller, L.S. (2014). Bias among forensic document examiners: Still a need for procedural changes. *Australian Journal of Forensic Sciences*, 46(1), 91-97.
- Tampa Bay Water v. HDR Engineering, Inc.*, 731 F.3d 1171 (11th Cir. 2013).
- Taroni, F., Marquis, R., Schmittbuhl, M., Biedermann, A., Thiéry, A., & Bozza, S. (2012). The use of the likelihood ratio for evaluative and investigative purposes in comparative forensic handwriting examination. *Forensic Science International*, 214(1-3), 189-94.
- Taroni, F., Marquis, R., Schmittbuhl, M., Biedermann, A., Thiéry, A., & Bozza, S. (2014). Bayes factor for investigative assessment of selected handwriting features. *Forensic Science International*, 242(1-3), 266-73.
- Turnbull, S.J., Jones, A.E., & Allen, M. (2010). Identification of the class characteristics in the handwriting of Polish people writing in English. *Journal of Forensic Sciences*, 55(5), 1296-303.
- United States v. Chiardio*, 684 F.3d 277 (1st Cir. 2012).
- United States v. Herrera*, 704 F.3d 480, 486 (7th Cir. 2013).
- United States v. Jones*, 107 F.3d 1147 (6th Cir. 1997).
- Will, E., (2012). Inferring relative speed of handwriting from the static trace. *Journal of Forensic Document Examination*, 22, 55-63.

Relationships between Handwriting Features and Executive Control among Children with Developmental Dysgraphia

Sara ROSENBLUM^a

^a. *The Laboratory of Complex Human Activity and Participation (CHAP), Department of Occupational Therapy, Faculty of Welfare and Health Sciences, University of Haifa, Mount Carmel, 3498838, ISRAEL*
rosens@research.haifa.ac.il

Objective: To describe handwriting and executive control features and their inter relationships among children with developmental dysgraphia, in comparison to controls. **Method:** Participants included 64 children, aged 10-12 years, 32 with dysgraphia based on the Handwriting Proficiency Screening Questionnaire (HPSQ) and 32 matched controls. Children copied a paragraph on paper affixed to a digitizer that supplied handwriting process objective measures (Computerized Penmanship Evaluation Tool–CompPET). Their written product was evaluated by the Hebrew Handwriting Evaluation-HHE. Parents completed the Behavior Rating Inventory of Executive Function (BRIEF) questionnaire about their child's executive control abilities. **Results:** Significant group differences were found for handwriting performance measures (HHE and CompPET) and executive control domains (BRIEF). Children with dysgraphia required significantly more performance time, wrote longer letters, erased significantly more and produced less organized written product than controls. 43% of the variability of *number of erasures* was explained by *working memory* and *abilities to organize materials* (BRIEF). Based on one discriminate function including handwriting performance and executive control measures, 98.4% were correctly classified into groups. **Conclusion:** Results strongly recommend consideration of executive control domains to obtain better insight into handwriting deficit characteristics among children with dysgraphia, to improve their identification, evaluation and the intervention process.

The Timing of Eye-hand Movements during Signature Simulations

Avni PEPE^a and Jodi SITA^b

^a *Physiology, Anatomy and Microbiology, La Trobe University
Bundoora*

3081, Melbourne, AUSTRALIA

^b *School of Allied Health, Australian Catholic University
Melbourne*

3000, Melbourne, AUSTRALIA

avnipepe@gmail.com, Jodi.Sita@acu.edu.au

Abstract. An investigation of the eye and hand movement during the task of signature simulation was conducted. Three subjects' eye movements and hand movements were recorded using an eye-tracker and a digitizing tablet while they simulated signatures. The study revealed that eye gaze most frequently shifted within less than 17 msec of a pen velocity minimum. It is thought that the cognitive processes overseeing this movement control and the limitations of the visuomotor buffer could play an important role in the behaviour of simulating signatures and signature simulation quality.

1. Introduction

The relationship between eye and hand movements during the task of signature simulation has not been thoroughly investigated previously, particularly with respect to movement initiation and termination. Previous research on line copying has found that the eyes tend to move within 33 msec of the pen reaching a velocity minimum (Pepe & Sita, 2014). It has been proposed that the eyes may be receiving feed-forward information about the upcoming movement (Ketcham et al., 2006; Reina & Schwartz, 2003), or that there is a reciprocal exchange of information between the sensorimotor systems (Vercher, Gauthier, Cole, & Blouin, 1997). Although it has been proposed that this close eye-hand relationship may help improve the spatial accuracy of signature simulations (Pepe & Sita, 2014), the question of whether this relationship is evident during the task of signature simulation has never been investigated.

Previous studies have also found that the eyes frequently lead the hand in motor tasks (see Gielen, Dijkstra, Roozen, & Welton, 2009; Inhoff, Briehl, Bohemier, & Wang 1992; Truitt, Clifton, Pollatsek, & Rayner, 1997). The eyes are thought to lead manipulative action by around half a second and move on to the next object about half a second before the action is completed (Land, 2006). The presumed role of this half second buffer is to hold information for a brief time period, allowing a match between episodic input and continuous motor output (Land & Furneaux, 1997). This buffer would therefore allow simulators to check, or guide their written output and to look back to the exemplar signature in a 'just-in-time' manner (see Ballard, Hayhoe & Pelz, 1995) to transform the next part of the exemplar signature into a motor program before the visual information in memory had faded, therefore allowing the motor action to proceed (Ballard et al., 1995; Hayhoe, Bensinger, & Ballard, 1998; Land, 2006).

It is therefore of interest to explore the timing of eye and hand movements to help determine behavioural processes underlying signature simulations.

2. Methods

A total of three subjects were tested. Subjects sat on a kneel chair at a table with an attached PTZ-1230 12x12 Wacom Intuos 3 digitising tablet (FFT low-pass 12 Hz filter capturing at 200 Hz with a sampling accuracy 0.25 mm in the x and y direction) and inking pen for recording subjects' raw and digital pen data. Movalyzer version 6.1 was used to capture digitising tablet data. A Tobii X-120 eye-tracker was attached and centered under the table facing upwards at an angle of 68° captured eye movements of subjects. The sampling rate of the eye-tracker was 100 Hz with a spatial accuracy of $\pm 0.5^\circ$. An external Basler scA640-120gc digital camera recorded the scene at 100 frames per second and allowed for viewing of simultaneous eye-gaze position and pen position.

The scene camera had a resolution capture of 658 x 492 pixels and was positioned directly above the center of the writing area. A blank, white screen was placed perpendicular to the table and positioned behind the digitising tablet to enhance luminosity to increase the reliability of the eye-tracking sampling. A head rest was used to keep subjects' head positions stable throughout testing to maximize eye-tracking spatial accuracy. Gaze data was recorded in Tobii studio version 2.0.2 and analysed in Tobii studio version 3.0.3.

Once seated, subjects were adjusted to a comfortable sitting height. The eyes' viewing distance from the eye-tracker ranged between 54 cm and 62 cm depending on subject height. At 57.3 cm, 1° of visual angle equated to 1 cm on the page. Following the eye-tracker calibration in which subjects were required to look at 5 fixed calibration points on a blank page, subjects were required to have a practice attempt at copying the word 'practice'. This was to ensure a comfortable writing position and to make sure that the eye-tracker was tracking

properly. Following this practice attempt, subjects were instructed to produce simulations of two different exemplar signatures.

Simulations were produced at least 5° below the exemplar, removing the ability of subjects to acquire visual information using parafoveal vision. An example of a completed signature simulation trial from the view of the scene camera is shown below in Figure 1.1.

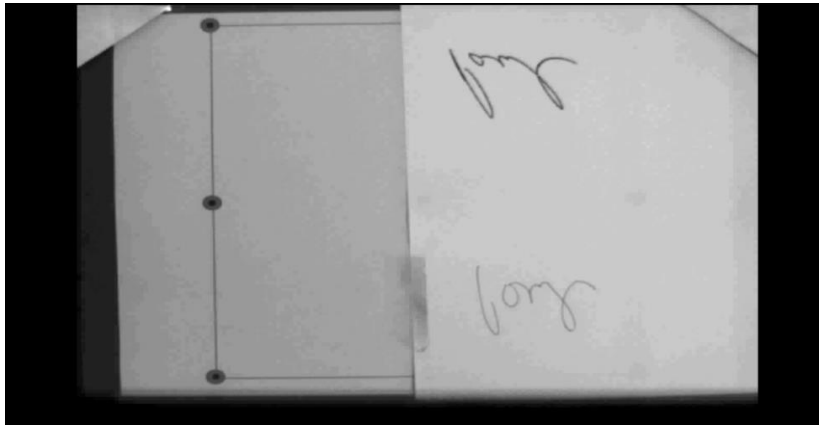


Figure 1.1. A completed simulation trial.

Subjects were instructed to simulate the exemplar to the best of their ability. Subjects were informed that they would begin each trial following a verbal cue and were required to move their pen away from the pad following completion of their simulation to indicate the end of the trial. Prior to commencing, and following their simulation attempts, subjects were required to look at a reference point.

Two different exemplar signatures were simulated three times consecutively by each subject. The order of presentation of the exemplars was counterbalanced between subjects, eliminating any bias effects due to fatigue or familiarity.

Gaze data was collected from first initial pen-down movement to completion of the final pen-down movement. The time differential between gaze shifts and velocity minima, as well as pen and eye lead times were extracted by viewing each frame captured by the video camera during the simulation trials.

Pen strokes produced during the simulation attempts were defined by peak velocity profiles in Movalzyer. These are represented by the lines between the circles in Figure 1.2. The circles represent the locations of pen velocity minima.

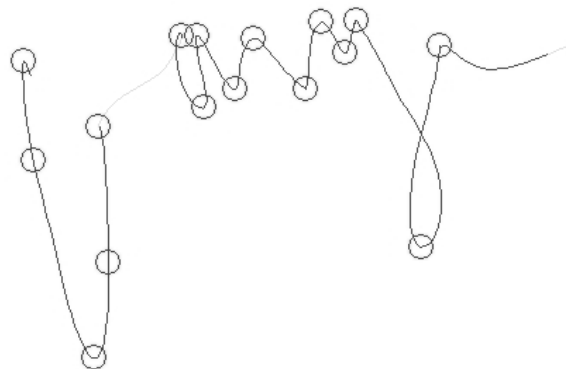


Figure 1.2. An image of a simulation trial showing the locations of velocity minima of the pen.

Gaze shifts that occurred when the pen was in-air were excluded from the analysis. In addition, when the pen was stationary, the only fixations included in the analysis were the fixations just prior to initial pen movement, or immediately after the pen movement had ceased. This was to control for excessive numbers of gaze shifts being made during moments the pen was stationary.

3. Results

The relationship between the observed gaze shifts and strokes are shown in Table 1.1. Lead-time referred to either i) the time that the eye led to pen (before the pen caught up to the position, or relative position of the eye), or ii) the pen led the eye (before the eye caught up to the position of the pen).

Table 1.1.
Summary of the eye and pen data for each subject during signature simulations

Subject	Average number of pen strokes produced	Average stroke duration (msec)	Average number of gaze-shifts made during pen-down movement	Average time gaze shift occurred from a pen velocity minima (msec)	Approximate average eye lead-time in front of pen (in strokes) on exemplar	Estimated eye lead-time (msec) on copy		Average number of strokes per gaze shift
						eye	pen	
1	13.0	191	7.00	39.6	2.18	419	n/a n/a	1.86
2	45.3	240	24.7	44.1	1.82	445	n/a n/a	1.83
3	35.2	212	8.50	41.8	n/a	n/a	418 604	4.10

There appeared to be a close temporal relationship between gaze shifts and pen velocity minima. The data revealed that this was not simply due to low average stroke durations. Gaze tended to shift most frequently within less than 17 msec of a pen velocity minimum. Figure 1.3 below shows a summary of the amount of time that elapsed between gaze shifts and pen velocity minima for the simulation trials.

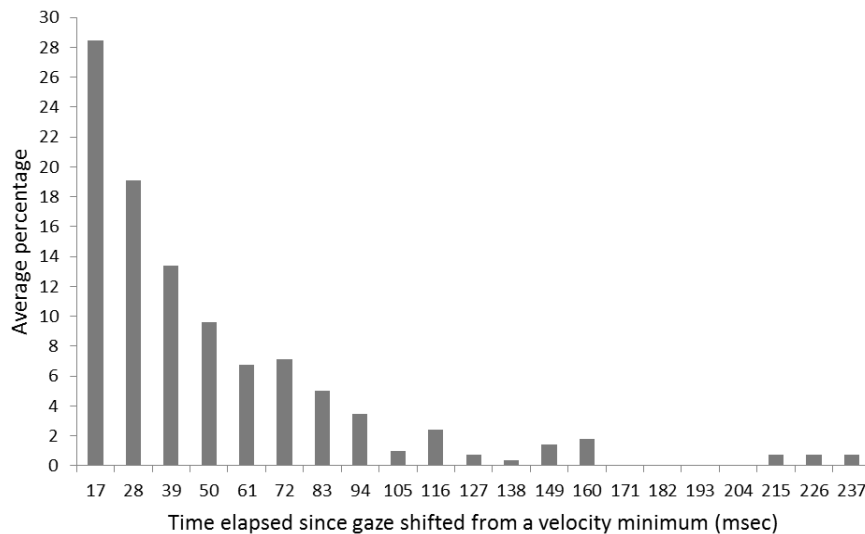


Figure 1.3. Average time elapsed between a gaze shift and a velocity minimum.

4. Discussion

The subjects' gaze frequently shifted around moments of pen velocity minima. This is evidence of a close temporal relationship between the eye and hand movements in relation to movement initiation and termination. Previous studies have reported similar relationships in tracing and drawing and other graphical tasks (Gielen, Dijkstra, Roozen, & Welton, 2009; Gowen & Miall, 2006; Ketcham et al., 2006; Reina & Schwartz, 2003). De'Seperati and Viviani (1997) suggest that there may be some general principles of operation common to the distinct modules responsible for setting up the motor output to the hand and the eye. It is possible that the timing of these movements serve to optimize the recurring cognitive processes involved in the task. From a quality of output point of view, this eye-hand behaviour makes sense. It seems logical to make gaze shifts at moments when the pen is moving slowest, as this allows adequate time for visual processing of the next stroke from the original image, or checking and/or guiding spatial output of the written trace. One presumed problem with making gaze shifts mid-stroke when the pen is moving quickly is that cognitive suppression (Irwin & Carlson-

Radvansky, 1996) and the time taken to visually process newly fixated area (see Rayner, 1998) may affect the accuracy of output by affecting the module responsible for setting up the motor output to the eye and hand.

There appeared to be occasional moments the eye would overshoot the position of the pen by close to half a second. Equally as often, the eye would lag behind the pen before making a saccade to catch back up to the pen's tip. Fixations following the pen on the line recently drawn may be part of a visual feedback mechanism controlling ongoing alignment of the pen with the pen trace and fixations made ahead of the pen are presumably used as a point of reference necessary to guide future pen movement (Tchalenko, 2007). The presence of these two eye behaviours suggests vision is able to adopt both a feedback and a feed-forward role during signature simulations.

The eye was observed to lead the pen by up to half a second when comparing pen position on the copy and eye position on the exemplar. This is likely to be necessary to transform visual information held in working memory into a motor program (Fleischer, 1986; Miall, Gowen, & Tchalenko, 2009). If information is held in a memory buffer for the time between a gaze shift and completion of the current motor act, the results would indicate that the memory buffer during this task is close to half a second long. This means that the simulator may only have half a second to fixate downward, guide the pen's movement and fixate back up to the exemplar in time to load the next stroke so that pen movement does not cease and line quality can be maintained. It is therefore suggested that the temporal limitation of the memory buffer is, in part, responsible for the commonly observed trade-off between the spatial quality and line quality during signature simulations.

Future studies should attempt to validate the current study's findings using a greater number of subjects and attempt to determine how the temporal limitations of the visuomotor buffer can affect signature simulation quality and experts judgments about authenticity.

References

- Ballard, D. H., Hayhoe, M. M., & Pelz, J. B. (1995). Memory representations in natural tasks. *Journal of Cognitive Neuroscience*, 7(1), 66-80.
- De'Sperati, C., & Viviani, P. (1997). The relationship between curvature and velocity in two-dimensional smooth pursuit eye movements. *J Neurosci*, 17(10), 3932-3945.
- Fleischer, A. G. (1986). Control of eye movements by working memory load. *Biol Cybern*, 55(4), 227-238.
- Gielen, C. C., Dijkstra, T. M., Roozen, I. J., & Welten, J. (2009). Coordination of gaze and hand movements for tracking and tracing in 3D. *Cortex*, 45(3), 340-355. doi: 10.1016/j.cortex.2008.02.009
- Gowen, E., & Miall, R. C. (2006). Eye-hand interactions in tracing and drawing tasks. *Hum Mov Sci*, 25(4-5), 568-585. doi: 10.1016/j.humov.2006.06.005
- Hayhoe, M. M., Bensinger, D. G., & Ballard, D. H. (1998). Task constraints in visual working memory. *Vision Res*, 38(1), 125-137.
- Inhoff, A. W., & Wang, J. (1992). Encoding of text, manual movement planning, and eye-hand coordination during copytyping. *J Exp Psychol Hum Percept Perform*, 18(2), 437-448.
- Irwin, D. E., & Carlson-Radvansky, L. A. (1996). Cognitive Suppression during Saccadic Eye Movements. *Psychological Science*, 7(2), 83-88. doi: 10.2307/40062915
- Ketcham, C. J., Dounskaia, N. V., & Stelmach, G. E. (2006). The role of vision in the control of continuous multijoint movements. *J Mot Behav*, 38(1), 29-44. doi: 10.3200/jmbr.38.1.29-44
- Land, M. F. (2006). Eye movements and the control of actions in everyday life. *Prog Retin Eye Res*, 25(3), 296-324. doi: 10.1016/j.preteyeres.2006.01.002
- Land, M. F., & Furneaux, S. (1997). The knowledge base of the oculomotor system. *Philos Trans R Soc Lond B Biol Sci*, 352(1358), 1231-1239. doi: 10.1098/rstb.1997.0105
- Miall, R. C., Gowen, E., & Tchalenko, J. (2009). Drawing cartoon faces--a functional imaging study of the cognitive neuroscience of drawing. *Cortex*, 45(3), 394-406. doi: 10.1016/j.cortex.2007.10.013
- Pepe, A., & Sita, J. (2014). Gaze-shifts and Pen Velocity Minima during Line Copying with Consideration to Signature Simulation. In M. Horsley, B. Knight, & R. Reilly (Eds.). *Current Trends in Eye Tracking Research* (pp. 101-106). Switzerland: Springer international. doi: 10.1007/978-3-319-02868-2
- Rayner, K. (1998). Eye movements in reading and information processing: 20 years of research. *Psychol Bull*, 124(3), 372-422.
- Reina, G. A., & Schwartz, A. B. (2003). Eye-hand coupling during closed-loop drawing: evidence of shared motor planning? *Hum Mov Sci*, 22(2), 137-152.
- Tchalenko, J. (2007). Eye movements in drawing simple lines. *Perception*, 36(8), 1152-1167.
- Truitt, F. E., Clifton, C., Pollatsek, A., & Rayner, K. (1997). The perceptual span and the eye-hand span in sight reading music. *Visual Cognition*, 4(2), 143-161.
- Vercher, J. L., Gauthier, G. M., Cole, J., & Blouin, J. (1997). Role of arm proprioception in calibrating the arm-eye temporal coordination. *Neurosci Lett*, 237(2-3), 109-112.

Stress and Motor Learning: Does the Presentation of Physical or Cognitive Stress Influence Motor Skill Acquisition?

Christopher A. AIKEN^a, Sarah B. ODOM^a and Arend A. W. A. VAN GEMMERT^a

^a *School of Kinesiology, Louisiana State University*

112 Long Fieldhouse

70803, Baton Rouge, LA, U.S.A.

caiken2@lsu.edu, sodom4@lsu.edu, and gemmert@lsu.edu

Abstract. Research on the effects of stress on motor performance has produced inconsistent findings. The neuromotor noise perspective attempts to explain these divergent results by suggesting that stress has activating properties on the motor-system that may result in decreased reaction times; however, the increased activation due to higher amounts of stress does also increase noise in the motor-system that needs to be filtered out resulting in possible increases of processing times. One area in stress research that has received little attention is the effects of stress on motor learning. The purpose of this study is to investigate the effects of stress on motor learning and how the neuromotor noise perspective may explain the results. 60 individuals practiced a graphical aiming task with either no stress (control), physical stress (PS), or cognitive stress (CS). Following practice, participants performed a retention test without the additional stressors and a transfer task in which the task was performed in a reverse order. Results suggest that CS was more detrimental to motor performance than PS or control ($p < .05$). CS also performed poorer during retention ($p < .05$) but not transfer ($p > .05$). This suggests that even though cognitive stress hinders performance, motor-learning may still take place. Results also suggest that cognitive stress is more detrimental to human motor performance than physical stress.

Subspace method with multi scale wavelet for identification of handwritten lines

Takeshi Furukawa

Forensic Science Laboratory, Ibaraki Prefectural Police Headquarters

Kasahara 978-6, Mito, 3108550 JAPAN

tfurukawa@ieee.org

Abstract. This article proposes a new indicator for handwriting examination in text independent framework. Experiments of writer identification are addressed using only handwritten short lines instead of a whole character. After preprocessing such as binarization and contours extraction, profiles of contours of handwritten lines were decomposed with fifth scales wavelet decomposition. As the result, we obtained indicators which showed qualities of handwritten lines such as smooth or jaggy. The indicators were analysed with Principle Component Analysis (PCA), and eigen vectors were obtained. In a phase of writer identification, using Kernel Orthogonal Mutual Subspace Method (KOMSM), subspace was calculated by the eigen vectors. The result obtained through the experiments was not enough to satisfy. In future works, the proposed method will be applied to whole handwritten characters.

1. Introduction

This article proposes a new indicator for handwriting examination in forensic science. Main method to identify individuals by handwriting in today is observing features of handwriting by eyes of document examiners. There are several problems in the conventional method because different features are selected in processes of identification by even in a same document examiner and by also between different those examiners. In that situation, it is proposed that methods to extract features using pattern recognition in computer science such as strokes directions, or start, end, cross points on coordinates of strokes (Franke, 2007). However, the above structural features of handwriting are visible by human naked eyes. As the result, it is easy for disguiser to imitate the genuine handwriting and to disguise the forgery. In addition, it is easy for even ordinary people to control their handwriting consciously in order to change their habit in handwriting.

To overcome the problem, we proposed a method to utilize almost invisible features such as depths and widths of strokes. It had already reported in a previous article that there was strong correlation between depths, widths of strokes and pen-tip force (Furukawa, 2012). Consequently, these indicators measured from handwriting reflected pen-tip movements. In addition, there were individual differences among subjects, in particular, of which widths and depths in strokes of handwriting at each four direction. In previous our articles (Furukawa, 2013), short lines of four directions were tested in experiments, because the set of Chinese characters contains a lot of kinds of characters which range from simple shapes to complicated those so that we are not able to obtain same kinds of handwritten characters to compare. In this difficult situation, we use text independent framework to overcome the difficulty using only short lines as shown in Figure 1. We also use wavelet decomposition to acquire the degree of qualities of handwritten strokes. In a field of character recognition, wavelet decomposition was widely used in handwriting analysis (Wen et al., 1996, Deng et al., 1999, and He et al., 2005). Also in a field of signal analysis, Mallat used zero-crossing points as indicators which were intersections between decomposed profiles and zero along y-axis (Mallat, 1991). In our previous work, we used the zero-crossing, the result of the work showed that eigen values of each three scale indicated individualities of each subject. The detail is shown in the previous article. In this our paper, however, we use the whole decomposed profiles instead of the zero-crossing because the zero-crossing is a useful feature which shows a degree of a fluctuation with a compact size, at the same time, there is lost information from a whole profile. To use the information, fifth whole decomposed profiles are analyzed. In addition, we improve a process of identification, i.e., applying subspace method. The experiment we conduct is to identify writers using several subspace methods such as Kernel Orthogonal Mutual Subspace Method (KOMSM). Subspace methods have been used in many areas such as face recognition. Superior points which subspace method has simple and easy implement for wide variety of real data in spit of data has multi classes. (Fukui et al., 2007, and Ohkawa et al., 2009). We explain details of our experimental methods in the following section. In the section of experimental results, we indicate potential of our proposed method. Finally, in the last section, we show the conclusion.

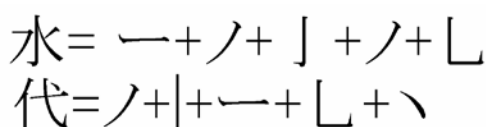


Figure 1. Conceptual diagrams of decomposition of whole characters to strokes.

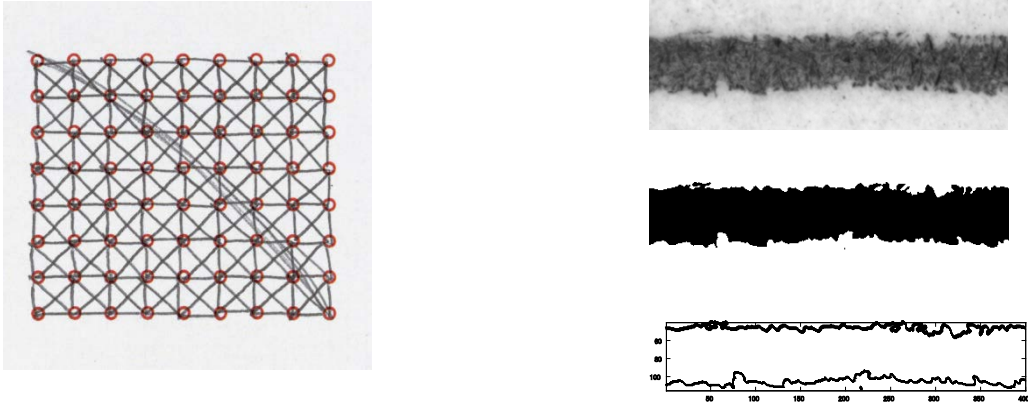


Figure 2. An image used in the experiment and pre-processing. The top column: raw image, the middle column : binary image, and the bottom column : contour image

2. Method

This article improves on identifying writers from written short lines which were composed of four directions of strokes using subspace method. Firstly, ten subjects (eight males and two females) were asked to draw short lines on a sheet of paper which was put on a digitizer tablet. The short handwritten lines were scanned by a flat bed type image scanner (Creo, iQsmart³) with high resolution (5400dpi). After binarization, using Otsu method (Otsu, 1979), contours of the short lines were extracted from the binarized handwritten lines as shown in Figure 2. Profiles were obtained by being subtracted from upper (right) contours to lower (left) contours. These profiles were determined to the features. The profiles were decomposed using fifth scales of wavelet decomposition. Finally, five decomposed profiles were extracted from the whole contours profile.

Firstly, the profiles were analyzed with PCA (Principle Component Analysis) in order to obtain eigen vectors among subjects. Secondly, test of identifying writers, between 20 training data and 44 trial data was yielded using several subspace methods such as Mutual Subspace Method (MSM), Kernel Mutual Subspace (KMSM), and Kernel Orthogonal Mutual Subspace (KOMSM). Kernel method is effective for recognition of objectives when a distribution of objectives has nonlinear structures.

In this section, the subspace methods are briefly explained. A common main idea is making subspaces which represent features of samples in low dimensions from learning samples. In learning stages, autocorrelation of sample data is calculated. Autocorrelation matrix is conducted by eigen extension so that eigen vectors are obtained. The subspaces are usually expressed as the eigenvectors. In stages of identification, similarities between objects to recognize and learned samples are estimated to be calculated inner products between vectors of objects to recognize and eigen vectors. Similarities are determined angles between input vectors and subspace, i.e., dictionary as shown in Figure 3. Mutual subspace method (MSM) also makes subspace from input samples to recognize as same as learning samples as shown in Figure 4.

$$\cos^2 \theta = \frac{\sum_{i=1}^N (\mathbf{p} \cdot \Psi_i)^2}{\|\mathbf{p}\|^2} \quad (1)$$

$(\mathbf{p} \cdot \Psi_i)$ denotes inner product between input vector. \mathbf{p} and i th denotes orthogonal base vector in dictionary subspace. $\|\mathbf{p}\|$ denotes norm of \mathbf{p} vector.

$$\cos^2 \theta = \max_{\substack{\mathbf{u}_i \perp \mathbf{u}_{j \neq i} \\ \mathbf{v} \perp \mathbf{v}}} \frac{(\mathbf{u}_i \cdot \mathbf{v}_i)^2}{\|\mathbf{u}_i\|^2 \|\mathbf{v}_i\|^2} \quad (2)$$

\mathbf{u}_i denotes i th input vector subspace, \mathbf{v}_i denotes i th dictionary subspace.

Orthogonal subspace method (OMSM) contains procedures that relationship among dictionary subspaces is orthogonal to improve ability of discrimination of classes. In using SM, MSM, and OMSM, similarities are defined the following equation.

$$\text{Similarity} = \frac{1}{N} \sum_{i=1}^N \cos^2 \theta \quad (3)$$

Recently, Fukui et al. proposed KOMSM as shown in Figure 5. This method is able to improve on conventional methods such as MSM, and OMSM. These conventional methods use multiple input vectors to increase accuracy meanwhile simple subspace method uses only a single input vector. As increasing numbers of class of input images, however, similarities among classes are also increasing so that accuracies were decreasing.

In order to overcome the defects of OMSO, the relationship among classes in dictionary space is orthogonal. Although OMSM has high accuracies to discriminate classes, the accuracy is decreasing when relationship among classes have nonlinear structures. For example, in individual face recognition system, directions of faces, facial expressions, and illumination conditions are changed in nonlinear. To adapt nonlinear data classes, KOMSM uses kernel trick so that nonlinear distribution is mapped to high dimension spaces to discriminate classes. Firstly, original pattern x in m th dimensions are mapped high dimensions nonlinear feature spaces using nonlinear transform ϕ .

$$\phi: x \rightarrow \phi(x) = (\phi(x_1), \dots, \phi(x_m))^T \quad (4)$$

In order to project maps in nonlinear spaces to nonlinear subspaces, it is necessary to calculate inner product between the map $\phi(x)$ and $\phi(y)$. It is difficult to calculate the inner product because there is data in high dimensions. Defined nonlinear transform ϕ through kernel function, $h(x; y)$, however, inner product, $(\phi(x) \cdot \phi(y))$ is able to calculate from original pattern vectors x and y . This is called kernel trick. For example, there is following Gaussian function.

$$h(x \cdot y) = \exp\left(-\frac{\|x - y\|^2}{2\sigma^2}\right) \quad (5)$$

Kernel Principal Component Analysis (KPCA) to pattern $x_i (i = 1, \dots, m)$ is attributed to eigen value problem of $m \times m$ matrix \mathbf{K} , i.e., kernel matrix which is obtained through kernel functions.

$$\begin{aligned} \mathbf{K} \mathbf{a} &= \lambda \mathbf{a} \\ k_{ij} &= (\phi(x_i) \cdot \phi(x_j)) \\ &= h(x_i, x_j) \end{aligned} \quad (6)$$

Base vector of i th, e_i in nonlinear subspace which is obtained from KPCA is expressed by linear summation of map of m 's learning pattern, $\phi(x_j)$.

$$e_i = \sum_{j=1}^m a_{ij} \phi(x_j) \quad (7)$$

a_{ij} is j th component of eigen vector, a_i which is correspond to i the largest eigen value, λ_i in kernel matrix, \mathbf{K} . This base vector, e_i is not able to directly calculate, however, inner products between components of projections in map, $\phi(x)$ or between base vectors are able to calculate. KOMSM uses the above parameters.

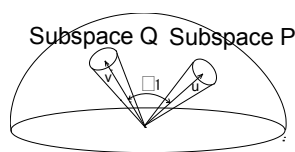


Figure 3. Conceptual diagrams of SM

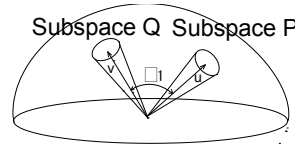


Figure 4. Conceptual diagrams of MSM.

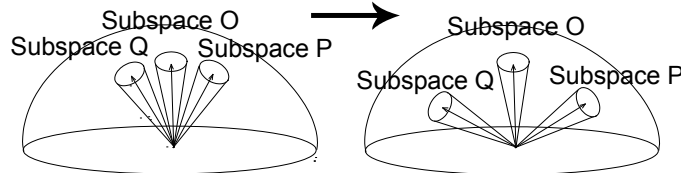


Figure 5. Conceptual diagrams of KOMSM.

3. Results

The results we conduct using several subspace methods are indicated in Table 1. The lowest equal error rate (EER) was obtained when KOMSM or KMSM was used, i.e., the EER was 0.440. The accuracy was not enough to identify the subjects. Figure 6 shows FRR and FAR of the experiment using KOMSM.

4. Conclusion and Future Works

We challenge an ideal method which is able to cover all kinds of characters that are composed of four directions strokes. The method we propose has possibility of being applied to not only same languages system but also different language system. In this work, however, the results were not satisfied for our document examiners. The reason why our method was failure was several causes such as not be considered orders of written strokes. One cause which we should point, in our experiments, subjects drew sequentially the only one direction, for example, firstly, they drew 64 horizontal strokes, next, 63 vertical strokes, 56 right-down and, finally, 56 left-down. If subjects drew in order of horizontal, vertical, right-down, and left-down at one time such as Chinese character ‘木’, we were able to obtain another results. Another cause we pointed is distribution of data which are detected from human writing movements. As shown in Figure 7, we were able to predict that distribution of handwriting which the subjects conducted contained nonlinear structures because the error rates of linear method such as MSM were lower than nonlinear method such as KOMSM. Consequently, we should find more robust method to classify handwriting. We will apply our proposed method to not only four directions lines but also normal characters such as Chinese characters and English characters.

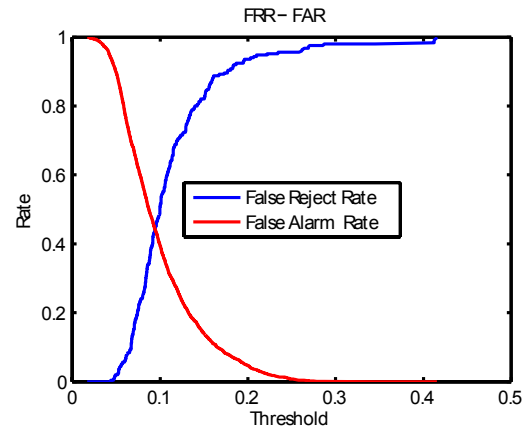


Figure 6. FRR and FAR of the experiment using KOMSM.

Table 1. The result of the experiment

Method	EER
SM	0.472
MSM	0.452
KMSM	0.440
KOMSM	0.440

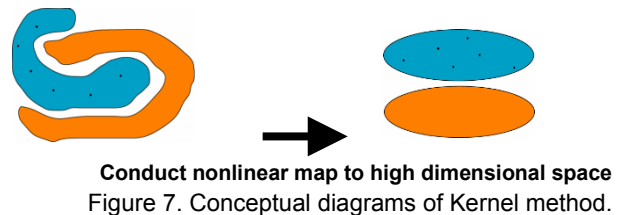


Figure 7. Conceptual diagrams of Kernel method.

Acknowledgement

This study was supported by KAKENHI(26919014-2014) from Japan Society for the Promotion of Science.

References

- Franke, K., Rose, S. (2004). Ink-deposition model: The Relation of Writing and Ink Deposition Processes. Prof. Int. Workshop. International Workshop on Frontiers in Handwriting Recognition – IWFHR’04, Tokyo (Japan), Oct. 26-29, pp. 173-178.
- Furukawa, T. (2012). The New Method of Identification of Handwriting Using Volumes of Indentations. Prof. Int. Conf. International Conference on Frontiers in Handwriting Recognition – ICFHR’12, Bari (Italy), Sep. 18-20, pp. 163-168.
- Furukawa, T. (2013). A Method of Evaluations of Handwritten Lines Based on Qualities of Contours Using Wavelet. Proceedings of the 16th Biennial Conference of the International Graphonomics Society, Nara (Japan), Jun. 10-13, pp. 159-162.
- Wen, C.J., Li, C., Jeng, B.S., and Yau, H.F. (1996). Tremor detection of handwriting Chinese Signatures Based on Multiresolution Decomposition Using Wavelet Transform. *Electronics Letters*, 32(3), 204-206.
- Deng, P.S., Liao, H.M., Ho, C.W., and Tyan, H. (1999). Wavelet-Based Off-Line Handwriting Signature Verification. *Computer Vision and Image Understanding*, 76(3), 173-190.
- He, Z., Fang, B. Du, J., Tang, Y.Y. and You, X. (2005). A Novel Method for Off-line Handwriting-based Writer Identification. Prof. Int. Conf. International Conference on Document Analysis and Recognition – ICDAR’05, Aug, pp. 242-246.
- Mallat, S. (1991). Zero-Crossings of a Wavelet Transform. *IEEE Trans. On Inf. Theory*, 37(4), 1019-1033.
- Fukui, K., Yamaguchi, O. (2007). The kernel orthogonal mutual subspace method and application to 3D object recognition. Proceedings of Asian conference on computer vision. pp467-476.
- Ohkawa, Y., Fukui, K. (2009). Hand shape recognition based on kernel orthogonal mutual subspace method. Proceedings of conference on Machine Vision Applications, pp122-125.
- Otsu, N. (1979). A Threshold Selection Method from Gray-Level Histograms., *IEEE Trans. on Systems, Man, and Cybernetics*, 9(1), 62-66.

Haar-like-features for query-by-string word spotting

Adam GHORBEL ^{a, b}, Jean-Marc OGIER ^b, Nicole VINCENT ^a

^a *LIPADE-SIP, Paris Descartes University*

75006, Paris, FRANCE

^b *L3i, La Rochelle University*

17042, La Rochelle, France

adamghorbel@hotmail.com

nicole.vincent@mi.parisdescartes.fr

jean-marc.ogier@univ-lr.fr

Abstract. This paper addresses the problem of word spotting in handwritten documents. The method is segmentation-free and follows the query-by-string paradigm. In the paper, we focus on the first step of the whole bio-inspired process that is based on two filtering steps, which are a global filtering followed by a more local filtering after a change of observation scale. The contribution of this approach is the use and the generalization of the Haar-Like-Features for the analysis of the document images, inspired from the famous visual perception principle. Different pieces of information are extracted from the whole image before drawing a conclusion, after a process of accumulation of votes. The method is evaluated using the IAM Handwriting Database.

1. Introduction

The automatic study of handwritten documents is a difficult task because of the very high variability of representation of the information. Indeed, the access to the content of these documents is linked to text recognition. The performance of Optical Character Recognition (OCR) engines is still poor, especially for handwriting recognition. One way to recognize the information within the document image is to look for some characteristic of the different words within it. For example a document may contain some significant words (e.g. information, request, and subscription), allowing the classification of the document without deciphering the totality of the document words. OCR does not present a complete solution to the problem because of its limitations in dealing with handwritings. In fact, OCR techniques cannot be accurately achieved because character recognition systems are not well suited for handwritings in an open vocabulary context. For that, word spotting is considered as an alternative to traditional OCR for different applications such as indexing and retrieval in digitized document collections. In the literature, ancient documents are mainly concerned by these word spotting questions, even a few trials on modern writings have been done.

In the literature, word spotting approaches have been applied to various scripts such as Latin, Arabic, Greek, etc. Word spotting approaches have been divided into different categories in multiple ways by document analysis researchers. For instance, they can be divided into two main categories based on matching techniques which are respectively image based matching techniques and feature based matching techniques (J.L Rothfeder, S. Feng, T.M. Rath., 2003). The former includes methods that compute word distances directly on image pixels using the correlation for the query matching. On the other side, the latter compute certain features for word images and then those features are matched. Another classification can be found in (J. Lladós, M. Rusiñol, A. Fornés, D. Fernández and A. Dutta, 2012) where two main approaches of word spotting exist depending on the representation of the query. These two types of approaches are based on Query-by-string (QBS) and on Query-by-example (QBE). The QBS methods (H. Cao and V. Govindaraju., 2007) use character sequences as input. They typically require a large amount of training materials since characters are *a priori* learnt, basically in HMM or NN models, and the model for a query is built at runtime from the models of its constituent characters. In QBE methods (R. Manmatha, C. Han, E. M. Riseman, 1996) the input is one or several exemplary images of the queried word. This is addressed as an image retrieval problem. Therefore, it does not require any training stage, but collecting one or several examples of the queried word. Another popular categorization technique divides the methods into either segmentation based methods or segmentation-free methods as in (T. Adamek, N.E. O'Connor, A.F. Smeaton, 2007) or in (B. Gatos and I. Pratikakis., 2009).

Based on the literature, we take into consideration the classification presented by the (J. Lladós, M. Rusiñol, A. Fornés, D. Fernández and A. Dutta, 2012) and we integrate it into the classification presented by both (T. Adamek, N.E. O'Connor, A.F. Smeaton, 2007) and (B. Gatos and I. Pratikakis., 2009).

In this paper, the aim is to find some words that are independently chosen from the document content. Particularly, if the processed documents do not contain many words, then a query by example is not possible. For that, we have chosen to express the query by a sequence of characters that is constructed by a keyboard input. This allows using our system in all circumstances, even if the word query is not present in any document images. In short documents, knowledge of word style could take too much time to be known, so the search for a word becomes a challenging problem. Furthermore, the aim is to avoid a training phase on a database to recognize graphemes or other entities in order to implement a word spotting system which is not only dedicated to one type

of documents. The genericity of the system requires designing a system that is capable of adaptation and self-learning. Thus, our method does not rely on a set of characteristics *a priori* fixed but on a family of features among which some will be selected in order to simultaneously fit the search term and the document properties wherein the research is performed.

The remainder of the paper is as following. In section 2, we introduce the family of operators applied in our work. Then in section 3, the proposed approach is detailed. Finally, section 4 is dedicated to the experimental results achieved with IAM database.

2. Generalized Haar-like-features

Looking at a word, it is recognized that human perception first considers to global view of the shape, before focusing on detailed parts. This depends on the observation scale. For example, the word “adam” that may be modeled by a global appearance looking like the pattern presented in Figure 1(f).

A word is characterized by intrinsic and exogenous characteristics. For instance, the number of letters, the position and presence of ascenders and descenders characterize the shape of each word. Besides, the size (width and height) of a character, which plays a major part in the construction of the different patterns, depends on the writing style in the documents to be processed. It is estimated by a size optimization using the Haar like feature of figure 1(l).

In a first step, we try to characterize the different patterns that may occur. This pattern characterization step is considered as an essential step of our approach because the final results depend on it. According to words in the document images, we can model a global view of each word by several patterns appearing simultaneously. Some of these patterns are illustrated in Figure 1. For example, Figure 1(g) represents a double ascender presence following by lowercase characters. Figure 1(b) can help in finding words similar to “adam”.

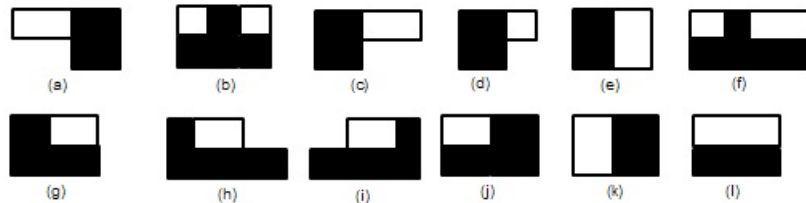


Figure 1. A few number of patterns applied in our work.

This approach is quite similar to Viola & Jones (P. Viola, M. Jones, 2001) approach that starts from a family of patterns and uses Adaboost to select some of them. It is more easy to use than Haar wavelet coefficients used in different document applications such as document text extraction (S. Audithan, 2009) or script identification (P. S. Hiremath, S. Shivashankar, 2008). In our case, the selection of the right patterns has to be done according to the word in order to retrieve it and according to the characteristics of the documents. Yet, we have generalized the patterns used in the Haar approach to fit the global shape of words written in Latin alphabet. The number of patterns and their shapes will define the query word and discriminate it from the other words. Furthermore, the more patterns applied, the better results are.

The patterns can be searched in the document using a convolution product between the image and a kernel containing 1, -1 or 0 values. The computation complexity is not too high when integral image is used. The operator enabling to detect a pattern P that is applied on the whole image will give a new image I_p , where the presence of the pattern is characterized by a high grey level. The filter can be applied in a blind way on the whole document and will automatically select the text lines where the answer to the operator will be high. At a lower level, similar patterns may be used to distinguish between an ‘o’ and a ‘c’, making evident the concavities.

This tool is the core of the approach we are proposing.

3. Proposed Approach

To process documents that present (i) a wide variability of style, (ii) ancient or modern with fragmented characters due to the non-homogeneity of the ink, (iii) crossing of lines, (iv) variability in writing style and (v) an above overlap of components such as components belonging to several lines of the text because of the presence of ascenders and descenders, we propose to consider the following major constraints:

- No layout segmentation: the query is directly compared to the whole document image components as it is very difficult to perform an accurate line, word or even character segmentation.
- No binarisation is required, which permits to avoid losing data in the pre-processing of document images.

Our approach globally looks at document images without any use of a word segmentation step, which is often assumed in current methods of Word Spotting. We introduce in our proposed approach two major phases:

- In the first one, at document level, in a global way, the search space is reduced to Zone of Interests (ZOI's) which are considered to contain Candidate Words (CW's).

- In the second one, a refining step enables to retain only the very similar CW's to the query.

The implementation of these two major phases relies on the same process, which can be considered as a filtering step applied sequentially at two different scales. These two bio-inspired steps (simulating the famous focusing perception principle) are based on the application of the Haar-like-features defined in previous section.

3.1 Document level

At document level, some zones of interest are selected; they are defined as the accumulation of specific patterns, in a limited and relative space. Each pattern, then each filter can be considered as a Viewpoint. The presence of these patterns is detected in the image I_p associated with the corresponding operator. The presence of the pattern is linked to a binarisation of I_p , where I is the original image in grey level. In fact as several patterns are associated with a word, several I_p images are available. The patterns associated with a word are in a limited area but their simultaneous presence is highlighted if the I_p images are translated according to the properties of the query word. Fusion of the filtered images is achieved by accumulation of the translated images. A binarisation process gives some hints at the position of words with same shape as query word. The position and area of patterns lead to the definition of the CWs. This Global analysis step represents the major and original step of our approach. It helps to limit the number of CW's and to obtain the CW's, which are the most similar to the query.

3.2 Word level

The overall filtering presented in previous subsection results in a large number of CW's that may correspond to the global shape of the query. This number is greater than the real number of the occurrences of the query in the document. In order to reduce the number of CW's, we introduce a second phase that is based on a refining filtering. Thus, we are going to change the observation scale. We concentrate our work at a lower scale, the word scale, rather than the previously used document scale. The candidates have approximately the same size (number of characters) as the query. However, we apply other new FW's on the selected ZOI's but handled by gradually changing the observation scale. This step aims at refining the results and improving the accuracy of the results. Finally, we obtain only the query occurrences existing in the processed document images.

The flowchart of our word spotting approach is highlighted in Figure 2.

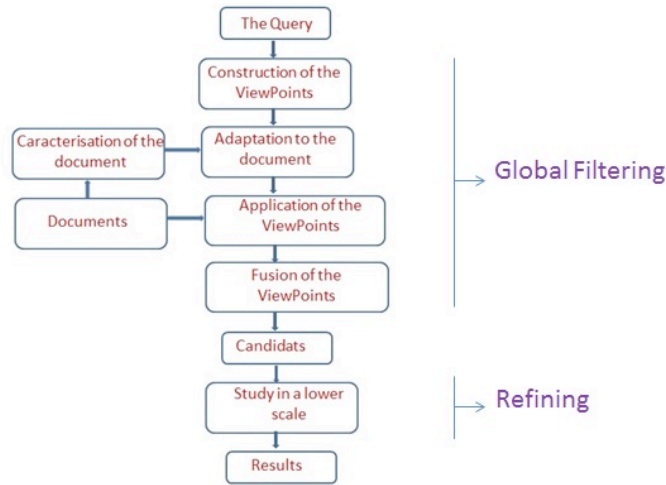


Figure 2. The flowchart of the proposed approach.

4. Experimental Results

Our approach has been evaluated on the IAM handwriting database consisting of 1539 pages written by 657 writers (U. Marti and H. Bunke., 1999) (U. Marti and H. Bunke., 2002). In our experiments, we have not worked on the isolated words but on the document images themselves. So, we work at document level. We randomly selected some document images and worked only on the handwritten texts. The performance is measured by using Precision and Recall criteria. Precision P is the percentage of the retrieved words that are relevant to users. Besides, Recall R is the percentage of the words that are same as the query and are successfully retrieved from the IAM Handwriting database.

$$R = \frac{\text{TotalSameWords Retrieved}}{\text{TotalSameWords Existing}} \times 100 \quad (1)$$

$$P = \frac{\text{TotalSameWords Retrieved}}{(\text{SameWords Retrieved} + \text{FalsePositives})} \times 100 \quad (2)$$

The evaluation of our work is based on Quantitative and Qualitative studies. We illustrate the results on three scripts written with three different styles extracted from the IAM database and shown in Figure 3. Here, the query word is “the”, a rather short, so difficult word to be spotted. We notice that the occurrences of the query have various lengths and widths in tested documents.

From our experiments, our approach is capable of finding all the instances of the queries in the tested document images. Thus, in most cases, the recall of our system is 100%. This extraction step loses very few positive answers. Furthermore, we notice that our approach detects other CWs for the query word that have almost the same shape or begin with letters having the same shape as the query. The precision strongly depends on the writing style. In Figure 3(c) the precision is 10%, in figure 3(a) it is about 48%, as a whole from 40 pages we have 21%. These low precisions can be improved by increasing the number of applied patterns.



Figure 3. Obtained results of some tested images.

5. Conclusion

In this paper, we have presented a word spotting method that does not rely on any previous segmentation step. This approach can be used in heterogeneous collections containing both handwritten and typewritten documents. We proposed new generalized Haar-Like filters and apply them to word modelling and spotting. The presented work is applied on the IAM Handwriting Database. In future works, we will focus on proposing a refining filtering phase in order to increase the accuracy of our word spotting approach.

References

- B. Gatos and I. Pratikakis. (2009). Segmentation-free Word Spotting in Historical Printed Documents. *In Proc. of the 10th Int. Conf. on Document Analysis and Recognition*.
- H. Cao and V. Govindaraju. (2007). Template-free Word Spotting in LowQuality Manuscripts. *In 6th Int'l Conf. on Advances in Pattern Recognition*.
- J. Lladós, M. Rusiñol, A. Fornés, D. Fernández and A. Dutta. (2012). On the influence of word representation for handwritten word spotting in historical documents. *International Journal of Pattern Recognition and Artificial Intelligence*.
- J.L Rothfeder, S. Feng, T.M. Rath. (2003). Using corner Feature Correspondences to Rank Word Images by similarity. *Conference on Computer Vision and Pattern Recognition Workshop*, pp. 30–35.
- P. S. Hiremath, S. Shivashankar. (2008). Wavelet based co-occurrence histogram features for texture classification with an application to script identification in a document image. *Pattern Recognition Letters* 29(9), 1182–1189.
- R. Manmatha, C. Han, E. M. Riseman. (1996). Word Spotting: A New Approach to Indexing Handwriting. *International Conference on Computer Vision and Pattern Recognition (CVPR)*, 631–637.
- S. Audithan. (2009). Document Text Extraction from Document Images Using Haar Discrete Wavelet Transform. *European Journal of Scientific Research ISSN 1450-216X*, 36, 502–512.
- T. Adamek, N.E. O'Connor, A.F. Smeaton. (2007). Word Matching Using Single Closed Contours for Indexing Handwritten Historical Documents. *International Journal on Document Analysis and Recognition*.
- U. Marti and H. Bunke. (1999). A full English sentence database for off-line handwriting recognition. *In Proc. of the 5th Int. Conf. on Document Analysis and Recognition*, 705–708.
- U. Marti and H. Bunke. (2002). The IAM-database: An English Sentence Database for Off-line Handwriting Recognition. *Int. Journal on Document Analysis and Recognition*, 5, 39–46.

Writer identification – clustering letters with unknown authors

Joanna Putz-Leszczynska
Warsaw University of Technology,
Faculty of Electronics and Information Technology
Nowowiejska 15/1900-665 Warsaw, Poland,
jputz@elka.pw.edu.pl

Abstract. This paper provides a simple algorithm for writer identification of historical letters. The collected database is an original historical database, of 100 pages belonging to 25 people selected from a 500 letters database. In the article there is presented an article for a cauterization of the letters, because the system doesn't have the templates of the classes and doesn't know how many classes is in the database. The obtained result shows that automatic identification can help historical experts to segregate the documents, before they would analyze the text information.

1. Introduction

Historical archives are an extensive collections of handwritten documents. A significant portion of these archives are being scanned and stored in electronic form in order to facilitate research. Many of the documents are not signed or associated with any author, whereas such association could be of benefit for researchers like historians or genealogists.

The aim of this work was to verify the effectiveness of automatic separation/ grouping by author of handwritten historical documents. In the literature, one can find a number of items related to verification of identity based on text (R. Messerli, H. Bunke) rather than a signature, but most of them work in controlled conditions - same ink color, guides etc . The present study, using the results so far published are a step further and examine whether these algorithms can to work on real pieces of writing, created under varying conditions, where the authors were in different positions, different places and different times of writing.

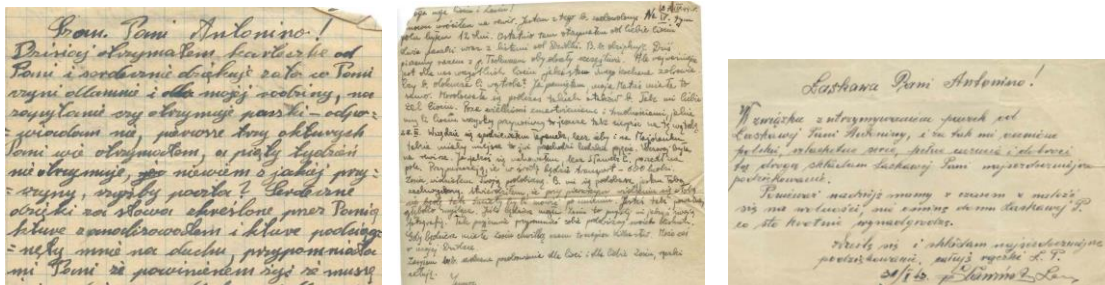


Figure 1 Examples of letters

In this paper, the research used a collection of approx. 500 letters - secret letters written from the Nazi concentration camp at Majdanek . This is one of many collections, which would facilitate an automatic segregation analysis and work with others. Some of the letters are quite clear and organized , written on a piece of lined paper (Figure 1). Others are more disorganized, where the disorder stems from lack of guides, or additional text which should be exempt from the characteristics extraction.

2. Database

As part of the work, 416 pages of secret messages from Majdanek have been scanned in 600 dpi and 300 dpi. In the second step, 25 classes have been selected, with 4 scans representing each scan. Only a part of a database was used, because only for this letters the 'clustering' by the human expert was done. The rest of the letters were postponed for further study as difficulties in identifying the class arose. An extended study would require assistance from handwriting experts. Finally the 300 dpi scans were used for study. The calculations were faster and 600 dpi did impact the results of the verification in a significant way.

3. Identification algorithm

The present algorithm consists of the following steps:

1. Pre- processing, where a color image is converted to a number of glyphs represented as binary image
2. Feature extraction, where using morphological operations are used to obtain 32 characteristics for each glyph.
3. Comparison based on clusters similarity distance

3.1. Pre-processing

The result of the preprocessing are glyphs, which are later used for feature extraction. An image in the RGB space is converted to a grayscale image. Next, **binarization** is performed using a dynamic threshold, which is determined for each image based on the mean value determined for this picture based on the gray-scale image. Next, **correction of image orientation** is performed.

For line segmentation, the author has decided to use a signal of the number of black pixels in each row of the image - lp as a function of r rows of the image (feature used in signature verification and proposed in [4]). This function has also been used to correct the orientation. To this end, for each image, a set of two graphs lp were calculated :

- Right hand side of the scan : : $lp_p(r)$ - black area on the scan Figure 5
- Left of the scan : $lp_l(r)$ - blue area on the scan Figure 5

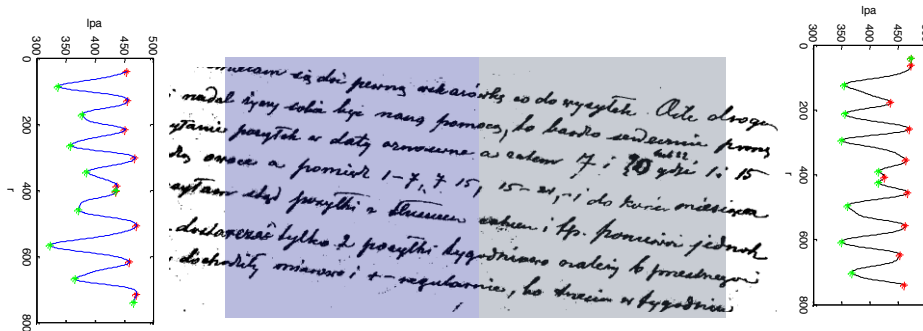


Figure 2 $lp_p(r)$ - black, $lp_l(r)$ - blue.

Each signal was smoothed using moving average over the signal. This algorithm has also been successfully used in studies of gait biometrics . This step simplifies the extremes detection in the signal. Equation (1) describes a moving average algorithm:

$$lpa(r) = \sum_{i=-k}^k w_i lp(r+i) \quad (1)$$

where:

- $2k + 1$ - the width of the time window
- w_i - samples weight
- $lp(r)$ - original data value at time t
- $lpa(r)$ - smoothed data value at time t

Each lpa signal is converted into an extremes vector (signal). The correction algorithm consists of choosing such a rotation angle where distance calculated using Dynamic Time Warping (DTW) between the signal extrema positions for the left and right side will be the lowest :

$$\vartheta = \arg \min_{\vartheta} D(ex_l, ex_p) \quad (2)$$

where D is the dissimilarity calculated using DTW .

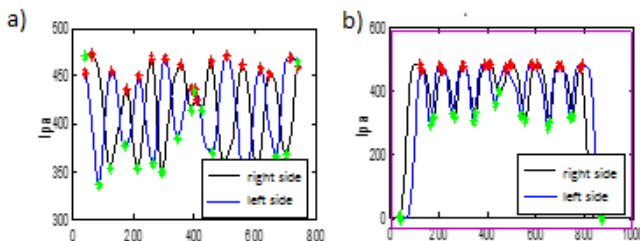


Figure 3 a) lpa signals for 0 degree b) lpa signals for 4 degree- the optimal correction

The result of this minimization can be seen in Figure 4 - the lowest value of $D = 1734$ is reached for 4 degree rotation. As a result of experiments, a -5 to 5 degrees range was determined.

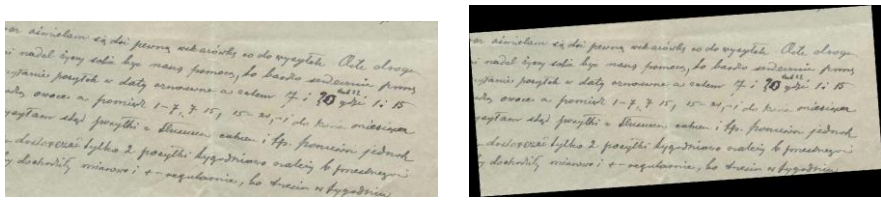


Figure 4 left: before correction, right: after correction

Then, the lp function calculated for the whole image is used for row segmentation using an experimentally set threshold (Fig 5).

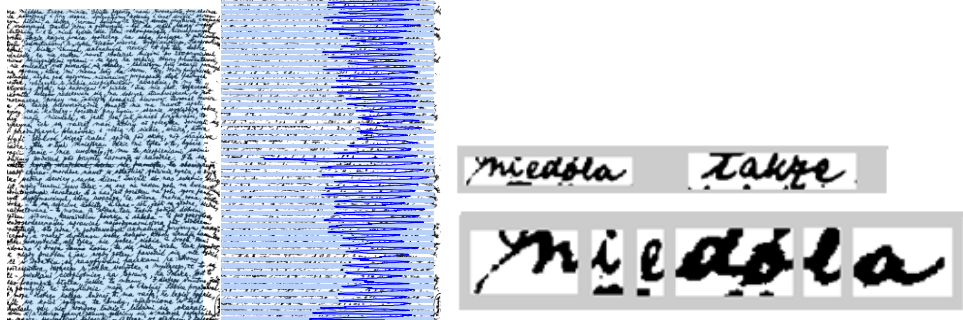


Figure 5 left: image segmentation into rows, right: rows segmentation into symbols

The rows segmentation into glyphs is realized by plotting the number of pixels, but this time as a function of the column number . The threshold, which is the parameter of the method determines whether the glyphs are whole words or individual characters/ groups of characters (Figure 5). After testing, the author decided to use the one that separates into individual characters – on average 215 symbols per page.

3.2. Feature extraction

A large number of feature calculation in off-line handwriting and signature verification has been proposed in the literature. Some are based on global features such as height or width of the symbol , others on the characteristics of texture. Some approaches try recreating the time of the formation of individual pen strokes and thus go to the field of signal processing (S. Chen and S. Srihari, P.S. Deng, H.-Y. Liao, B. Fang, C.H. Leung).

The aim of the study was to verify whether or not user grouping is possible in real data . For this reason, the author chose the features proposed in the paper (J. Fierrez-Aguilar et al.), which was further elaborated by the author in (Putz et al.). The proposed approach uses morphological operations. For each glyphs, features are determined by the steps of :

- a) Dilation- feature is the number of pixels lit after morphological dilation. Dilation of that element is performed five times and each time the number of pixels is recorded. As a result, a single structural element is used to designate exactly five features. Thus, as a result of operations using 4 structural elements, we get the 20 features.
- b) Erosion - feature is calculated as the number of pixels lit after morphological erosion. One structural element is used exactly once per original symbol giving only one feature . Hence, for the 16 structural elements we get 16 features.

In summary, the scan is converted to a set of glyphs, each represented by 36 features. This can be regarded as a collection of points in 36 dimensions.

3.3. Comparison

The comparison measure denotes a similarity between sets of clusters. Each scan, or a collection of points in 36 dimensions, is subjected to clustering using K-means. A clustering method with a preset number of clusters was selected deliberately, based on the assumption that the number of clusters, or groups of glyphs for handwriting in general should be constant. The task here is to compare two sets of clusters - one of which belongs to a scan looking for class, the second is a representative of the class to which it is compared. In the paper (M Hayvanovych et al.) has proposed a method of comparing symmetric clusters. In the presented solution it was decided to propose the asymmetric form of the formula. The reasoning was that in the case being considered, the first set of clusters suspected of belonging to a class $C_q = \{S_1, S_2, \dots, S_R\}$ is compared to the second set of clusters (class representative) $C_j = \{S'_1, S'_2, \dots, S'_R\}$. The value of dissimilarity between to clusters is determined as the sum of distance between centroids of clusters assigned to each of the two sets. In other words, for each cluster

from a set of scan verified $S_i \in C_q$, the distance is determined in 36 -dimensional space between the centroid and centroid S_i nearest cluster from a set of clusters being compared C_n class . Finally, the dissimilarity value is:

$$d(C_q, C_n) = \sum_{i=1}^K \min_{j=1, \dots, K} |S_i, S'_j| \quad (3)$$

3.4. Results

The following tests were carried out using two indicators :

- EER (Equal Error Rate) – equal error rate of false acceptance and false rejection
- ANE (Accepted No Error) - indicating the effectiveness of the correct assignment element (glyph) to the group in the absence of misallocation the group

Tests were conducted to select the best parameters. Here I present one that shows the relation of number of clusters to identification efficiency. As it is presented here, the best results were obtained for 2 clusters.

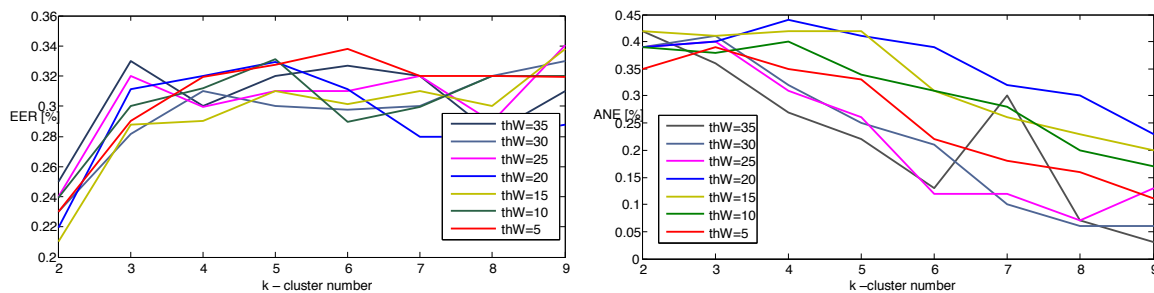


Figure 6: The EER and ANE results for different thW and cluster number.

Additionally, plots for different thW are presented – it is visible that the low thW gives the best results – the individual letters/ groups of letters. The best results obtained are EER ~ 20 % and ~ 45% of the ANE. Both results are very good. In particular, the EER result demonstrates a correct implementation- the result is similar to the ones reported in literature for handwritten signature verification are at this level. The ANE 45% success rate means that almost half of the scans were assigned properly without committing an error.

4. Summary

An algorithm was proposed, implemented in a computer program used to categorize handwritten documents. From the collection of 500 letters, secret messages from the Nazi concentration camp, 100 were selected, belonging to 25 people (4 for each person). The proposed algorithm was applied on the scanned letters, leading to the transformation of a letter in a set of glyphs, then used one of the many well-known approaches for determining the characteristics of the handwriting, features based on morphological transformations. The calculated features were used in a comparison algorithm based on the grouping of clusters. The results achieved error-free or 50% of the group assignments are a good prelude to broader studies involving forensic experts involved in writing, who would do a handmade categorization of the current base, making it possible to use the other 400 letters.

References

- H. Baltzakis and N. Papamarkos. A new signature verification technique based on a two-stage neural network classifier. *Engineering Applications of Artificial Intelligence*, 14:95–103, 2001.
- S. Chen and S. Srihari. Use of exterior contours and shape features in off-line signature verification. *Document Analysis and Recognition*, 2005. Proceedings. Eighth International Conference on, pages 1280–1284, 2005.
- P.S. Deng, H.-Y. Liao, C.W. Ho, and H.-R. Tyan. Wavelet-based off-line signature verification. *Computer Vision and Image Understanding*, 76(3):173–190, 1999.
- B. Fang, C.H. Leung, Y.Y. Tang, K.W. Tseb, P.C.K. Kwokd, and Y.K. Wonge. Offline signature verification by the tracking of feature and stroke positions. *Pattern Recognition*, 36:91–101, 2003.
- J. Fierrez-Aguilar, N. Alonso-Hermira, G. Moreno-Marquez, and J. Ortega-Garcia. An off-line signature verification system based on fusion of local and global information. *Workshop on Biometric Authentication*, Springer LNCS-3087, pages 295–306, 2004.
- M. Hayvanovych, M. Magdon-Ismail, Measuring Similarity between Sets of Overlapping Clusters , *Social Computing (SocialCom)*, 2010 IEEE Second International Conference on, pages 303 – 308, 2010
- R. Messerli, H. Bunke, Writer identification using text line based features *Document Analysis and Recognition. Proceedings. Sixth International Conference on*, pages 101 – 105, 2001
- J. Putz-Leschczynska, M. Chochowski, L. Stasiak, R. Wardzinski, and A. Pacut, Two-stage classifier for off-line signature verification, *13th Biennial Conference of the International Graphonomics Society*, Melbourne, Australia, pages 138–141, 2007.

An assessment of dynamic signature forgery creation methodology and accuracy

Luiz Felipe BELEM DE OLIVEIRA and Richard GUEST
School of Engineering, University of Kent, Canterbury, Kent, UK, CT2 7NT
r.m.guest@kent.ac.uk

Abstract. Signatures provide a convenient and widely accepted method of authentication, however they are prone to attack by forgery. This can be mitigated to an extent by analysing both the static and dynamic biometric aspects of construction, however the possibility for accurate forgery from a static image of a genuine signature still exists. In this study we explore initial forgery accuracy of a range of genuine signatures and how accuracy changes as a forger receives feedback from a commercial signature engine in terms of a 'match score'. We also explore the effects of genuine signature complexity on forgery performance alongside the image size of the genuine signature to be forged. Our results show that forgers are able to improve performance over time on simple signatures (including those with less pen travel distance) and that a magnified genuine sample enables more accurate forgery for these class of signatures. More complex signatures result in lower forged verification scores and irregular patterns of improvement across the five forgeries. Overall verification match scores were typically less than 80% for most attempts regardless of signature complexity, thus indicating the resilience of dynamic systems to unskilled forgery attempts.

1. Introduction

Signatures are a widely used form of behavioural biometric authentication. They have the advantage over other biometric modalities as being an acceptable and pervasive form of identification, being legally admissible in terms of formal authentication and exhibit intentional ceremony in sample donation (Impedovo et al., 2008). Most signature samples are written directly on a sheet of paper (or other signing surface) using a pen and are checked/verified by human inspection of the completed signature. This *static* form of assessment may be automated in a computer-based analysis using image processing and measurement techniques (Chapran et al. 2008). Conventional computer-based signature biometric systems use a combination of these static assessments and *dynamic*, or temporal, elements of signature construction. To enable a dynamic analysis requires the collection of signatures on a tablet device that samples pen position (and other data) at regular intervals. It has been shown that verification performance can be enhanced by combining both static and dynamic features (Jain et al, 2002). Signature however does have the disadvantage that samples can be relatively easy to forge, particularly in the static form. Very often a forger will be able to access a static image of the signature being forged whilst the learning process occurs, providing the ability to study both the shape of the signature and also to infer dynamic aspects of the signature construction such as stroke order, pen pressure and speed (Guest et al, 2009).

Assessing the forgery creation process using a dynamic method allows us to see how a forger adjusts production to achieve more accurate results in terms of a closer match to a genuine signature. In this study we assess how forgers modify their forgery behaviour given a static model of a signature and dynamic feedback on the forgery score between attempts. By using a number of source signatures of varying complexity it is possible to identify a) the dynamic performance at an initial forgery attempt, b) the effect of complexity on the ability to form an accurate forgery and c) how dynamic performance changes as feedback is provided. Feedback is only given in the form of an accuracy match score, without information such as velocity or pressure profiling, thereby replicating a conventional dynamic forgery scenario. Furthermore, by using a magnified genuine static sample as a model, we can assess the effect of physical sample size on forgery performance.

2. Methodology

The initial stage of the investigation involved obtaining a series of genuine source signatures that were used as models for forgery. Nine subjects agreed for their signature to be used for this purpose. Each of the nine subjects donated six signatures as dynamic enrolments to a commercial dynamic signature verification server system (which, for the purposes of this experiment, was treated as a black-box system). An internal checking process within the server ensured the stability of the donated signatures in forming an enrolment template. Signatures were captured using a back-projected LCD signature tablet (a Wacom STU-300) that provided virtual ink to the signing process. Signers were also asked to sign on a sheet of paper using a *biro pen* to provide a static signature in a format replicating a conventional pen-on-paper donation methodology. A second stage involved a static signature image from each of the enrolled nine signers providing the source signatures was categorised by 10 independent assessors as being either simple, medium or complex on the basis of 'difficulty to forge'. These 10 assessors were separate from the nine providing the model signatures. Categories were assigned by assessing the modal category given to each signature. Figure 1 shows the finalised categories of each of the source

signatures. The authors' note that legibility of text seems to be the primary driver for assigning to the simple group, whereas complex signatures tend to be symbolic representations of a name and contain a potentially unclear ordering of pen strokes. Assessing the complexity responses there was generally a high agreement between assessors *resulting in a clear modal response for each signature*.

The third phase of the methodology was to assess the forgery performance of a group of subjects (forgers). A total of 15 forgers took part in the experiment. These subjects were not part of the pool of subjects that donated source signatures or took part in the signature complexity categorisation. Each forger undertook the following protocol:

1. Presented with a randomly selected static 'model' image (from the biro-based collection) of a signature from the 'simple' pool, the subject is able to spend as long as they require studying the signature. The biro-based collection was used to replicate the conventional method of finding a signature to forge.
2. The forger tries to forge the signature using the verification system, signing on the STU-300 device.
3. The verification system provides a verification score, based on dynamic and static information, of between 0 (no match) and 100 (maximum matching). The forger used this score to assess their performance and encouraged to improve their verification score indicating an enhancement to the forgery.
4. The forger makes four more attempts, the score feedback being provided for each attempt.
5. Steps 1-4 are repeated for a different randomly selected 'simple' signature but with the 'model' image quadrupled in size, replicating examination under magnified conditions.
6. Steps 1-5 are repeated for two signatures (one normal sized, one magnified) from each of the 'medium' and 'complex' groups.



Figure 1: a) Simple 1,2 and 3, b) Medium 1, 2 and 3, and c) Complex 1, 2 and 3 Source Signatures

Results were analysed by assessing the performance of forgers on each of the signatures across multiple attempts and model sizes. The analysis focuses on overall performance in terms of verification thresholds, improvements over time and the effect of signature complexity on ability to forge. Full ethical approval was granted for this study.

3. Results

Figure 2 show the individual verification score results from the three *simple* signatures. In each of the charts the five sequential attempts of the five forgers (F1-F5) that were randomly selected to forge each signature are shown, initially using a standard sized genuine model signature, followed by a magnified model signature. It can be seen that, in most cases, a forger was able to improve their performance across the five attempts. Indeed, examination of Figure 3, which details the average performance for each attempt on each simple signature, shows this improvement. It can also be seen that for two of the signatures (Simple 2 and 3) the large/magnified signature produced a higher performance. The only constant factor that seems to determine match score is the amount of attempts that the forger produces a signature. It is also important to note that in general most forgeries were below a match score of 80%. In imposing such a threshold it is possible to demonstrate the effectiveness of the dynamic engine to distinguish between forgeries and genuine signature even on signatures deemed to be "simple" in complexity.

Figure 4 shows the results of the *medium* signature verification scores, whilst Figure 5 indicates the average performance across the three signature for the two sizes of model signature (note that there was only

four forgery attempts for these signatures). Here it is clear that the best results were obtained when the forger was copying from a real sized model signature. It is also possible to note that, compared to the simple signatures, the average scores related to medium signatures is relatively flat and thus not directly related to the amount of attempts that the forger undertakes. It can also be noted that for Medium Signatures 1 and 3, which have relatively lower ink travel length, the ability to obtain a high verification score (and hence successfully verify on the system) is enhanced. It is seen that an average score is maintained for all the attempts when dealing with a normal size image. However when the forger is viewing a magnified model image, the verification scores are not as stable as when copying from a normal size image. The amount of detail that is shown in a magnified image of a medium signature may affect the way the forger approaches their copy, leading to poorer results.

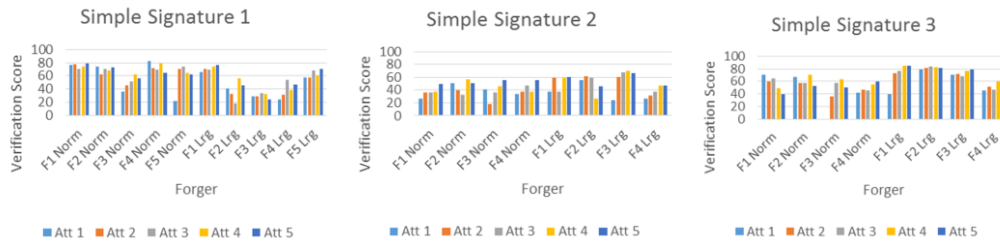


Figure 2: Simple Signature Attempts (Norm=Normal modal size, Lrg=Magnified model size, Att=Attempt)



Figure 3: Simple Signatures – Average Verification Score per Attempt

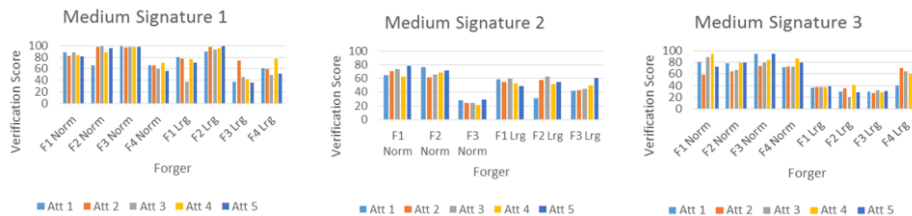


Figure 4: Medium Signature Attempts

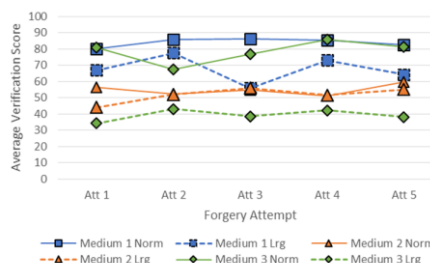


Figure 5: Medium Signatures – Average Verification Score per Attempt

Complex signatures are, in theory, the hardest to analyse and forge. By examining Figures 6 and 7 it can be seen that each signature has its own level of ability to be forged. Assessing the attempts using Complex

Signature 2 it is possible to establish that forgers produce a signature a similar profile to those in the Medium group – indeed this signature contained lower ink travel distance and thus is directly comparable to Medium Signatures 1 and 3. The average scores also vary considerably across attempts indicating that the forger is trying to copy the signature by trial-and-error. Analysing the average scores obtained for Complex Signature 1 the results show that the number of attempts for this signature is not too important, since both graphs indicate little improvement over the five attempts. It is interesting to see that in this case the size of the model signature does not have an effect on performance, as normal and magnified signatures produce interchangeable results. Complex Signature 3 is the hardest to assess. It is possible to see an enhancement of verification scores but the low values associated with these attempts shows the difficulty associated with forging this signature.

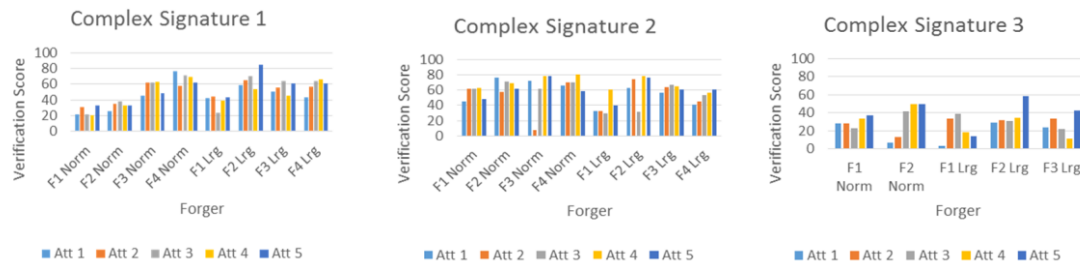


Figure 6: Complex Signature Attempts

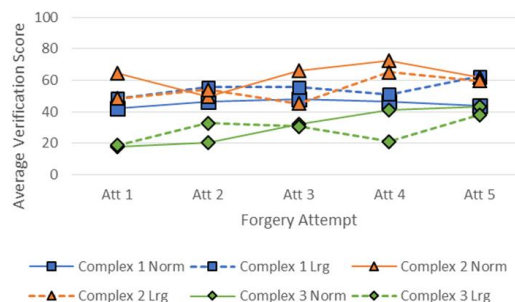


Figure 7: Complex Signatures – Average Verification Score per Attempt

4. Conclusions

The main conclusions from this study are:

- Perceived ease of forgery seems to be related to the readability of the signature.
- Signatures rated as *simple* show improvement across the five attempts with forgers being able to produce more accurate results using magnified images.
- Overall verification match scores were typically less than 80% for most attempts regardless of signature complexity.
- Signatures containing less ink were typically easier to dynamically forge.
- Complex signatures result in lower forged verification scores and irregular patterns of improvement across the five forgeries.
- For more complex signature the size of the source signature does not modify overall performance.

This study has also pointed to unskilled levels of forgery performance which can be incorporated as thresholds within dynamic signature engines. Future work will analyse the dynamics of the changes made by the forgers between attempts to identify patterns relating to perceived accuracy enhancements made.

References

- Impedovo, D., & Pirlo, G. (2008). Automatic signature verification: the state of the art. *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on*, 38(5), 609-635.
- Jain, A. K., Griess, F. D., & Connell, S. D. (2002). On-line signature verification. *Pattern Recognition*, 35(12), 2963-2972.
- Guest, R.M, Fairhurst, M.C., Linnell, T, Towards an Inferred Data Accuracy Assessment of Forensic Document Examination Methodologies for Signatures, In Proc. IGS 2009, Dijon, France, September 2009
- Chapran, J., Fairhurst, M. C., Guest, R. M., & Ujam, C. (2008). Task-related population characteristics in handwriting analysis. *Computer Vision, IET*, 2(2), 75-87.

Universum Learning for Semi-Supervised Signature Recognition from Spatio-Temporal Data

Lukas TENCER ^a, Marta REŽNÁKOVÁ ^a and Mohamed CHERIET ^a
^a *École de technologie supérieure (Département de Génie de la Production Automatisée)*
1100 Rue Notre-Dame Ouest
H3C 1K3, Montreal, CANADA

Abstract. We present a novel approach towards signature recognition from spatio-temporal data. The data is obtained by recording gyroscope and accelerometer measurements from an embedded pen device. The idea of Universum learning was previously presented by Vapnik and recently popularized in machine learning community. It assumes that the decision boundary of a classifier lies close to data with high uncertainty. The quality of the final classifier strongly depends on a way how to choose the Universum data and also on the representation of original data. In our paper we use a novel approach of Universum learning to classify signature data, also we present our novel idea how to sample the Universum data. At last, we also find more effective representation of the signature data itself compared to the baseline method. These three novelties allow us to outperform previously published results by 4.89% / 5.58%.

1. Introduction

Signature is a unique identifier which is used by millions of institutions and agencies to authenticate people. Over the ages, it served as one of the main ways to acknowledge a contract or an agreement. Despite modern advances in biometrics, signature is a prevailing means of unique identification. Because of this, to classify a signature is an essential task for biometrics and other security applications.

Besides visual information, a signature itself captures also a lot of additional data, which are not captured as a final result recorded on a paper or a digital medium. Specifically it is a way how the signature is drawn. Small aspects like tilt of the pen, acceleration over segments of the signature or order in which are elements of the signature drawn could provide essential insight into signee's identity. Because of this we rely on these rich data and we develop an algorithm, which can identify a user based on these data. Specifically we are talking about information captured from accelerometer and gyroscope devices. This approach is even more justifiable if we think about mass production and spread of mobile devices with embedded sensors to gather acceleration and orientation data, which enable collection of data for signature verification if the signature is made while holding the phone.

Once we are able to collect rich input data, we can further think also about algorithms for classification and how to improve them. Our aim is to use the popular semi-supervised learning methods, which can capture a structure hidden in the data and impose additional assumptions on the structure of the data. One of the very recent ideas was introduced by Vapnik and is called Universum learning. It relies on Universum examples and forces the decision boundary to be close to these examples (see Figure 1). Our approach can benefit from this additional assumption and basically gain “free” increase in performance. How “free” it really is, we will discuss further in the paper. Nevertheless, the improvement in performance is significant enough to be considered a serious improvement compared to the last published results on the same dataset (Griechisch, Malk, & Liwicki, 2013).

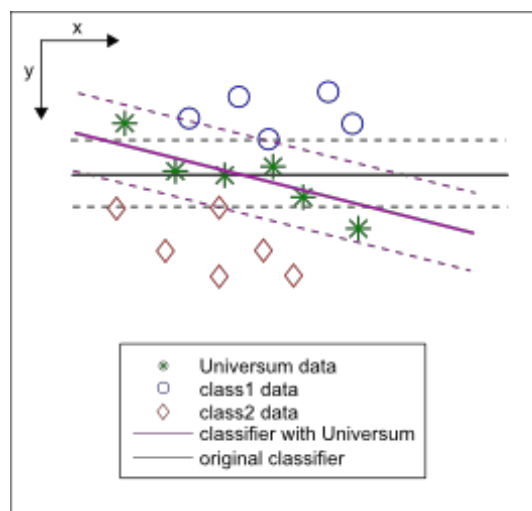


Figure 1: Illustration of Universum learning and change of the decision boundary based on Universum data (Dhar, 2014)

The general overview of works regarding signature classification could be found in (Impedovo & Pirlo, 2008) (Weiping, Xiufen, & Kejun, 2004) and (Wu, Jou, & Lee, 1997). Further works which regard specifically accelerometer and gyroscope data could be seen as early as (Plamondon & Parizeau, 1988) (Baron & Plamondon, 1989) or (Rohlik, Mautner, & Matousek, 2001) (Mautner, Rohlik, Matousek, & Kempf, 2002). More recent approaches which use spatio-temporal data are (Bashir, Scharfenberg, & Kempf) (Bunke, Csirik, Gingl, & Griechisch, 2011) (Shastri, Burchfield, & Venkatesan, 2011) and (Malik, Ahmed, Dengel, & Liwicki, 2012). One of the most recently published approaches, which uses Legendre series and SVM is (Griechisch et al., 2013) and is also the source of our dataset and our baseline technique. The Universum learning works were originally proposed by Vapnik and the theory was further expanded in (Weston, Collobert, & Sinz, 2006) (Sinz, Chapelle, Agarwal, & Schölkopf, 2008) (Cherkassky, Dhar, & Dai, 2011) and (Dhar, 2014). At last an overview of active learning techniques could be found in (Settles, 2010) and QbC is more specifically described in (Seung, Opper, & Sompolinsky, 1992)

This paper is structured as following: Section 2 describes our general methodology, Section 3 presents our experiments and achieved results and in Section 4 we conclude and discuss our work and outline future work.

2. Methodology

Our approach does have a structure of a standard pattern recognition pipeline, that means: feature extraction, learning and classification. One additional step which is present is the generation of Universum examples. This step comes during before the learning phase and a way how Universum examples are generated is essential for performance of Universum learning.

In a first step, we extract the features from the sequential signature data. Prior works (Griechisch et al., 2013) (Parodi, Gómez, & Liwicki, 2012) used Legendre series for the approximation. But based on our preliminary experiments we have selected Hermite polynomials which do have a form:

$$p(x) = c_0 + c_1 H_1(x) + \dots + c_n H_n(x); H_n(x) = n! \sum_{k=0}^{\frac{n}{2}} \frac{(-1)^k}{k! (n-2k)!} \frac{x^{n-2k}}{2^k} \quad (1)$$

This choice improved the performance of the algorithm by ~0.5-0.7%. Other polynomials which we evaluated were Legendre and Chebyshev polynomials.

Once we extracted the features, we need to generate the Universum examples. The most common approach how to generate Universum examples is the random averaging. This method is designed for a binary case but could be easily generalized to multi-class case using one-against-all or one-against-one strategy. The random averaging selects a sample from the positive and negative class and then averages their respective feature values individually. This approach is feasible in cases, the linear transition along the features axes yield similar results to the input elements. But this is not always the case with polynomial approximation. A small change in the value of polynomial coefficients might result in quite a different example if reconstructed from these coefficients. Because of this we decided to use active learning method Query-by-Committee to select the relevant examples for the Universum class.

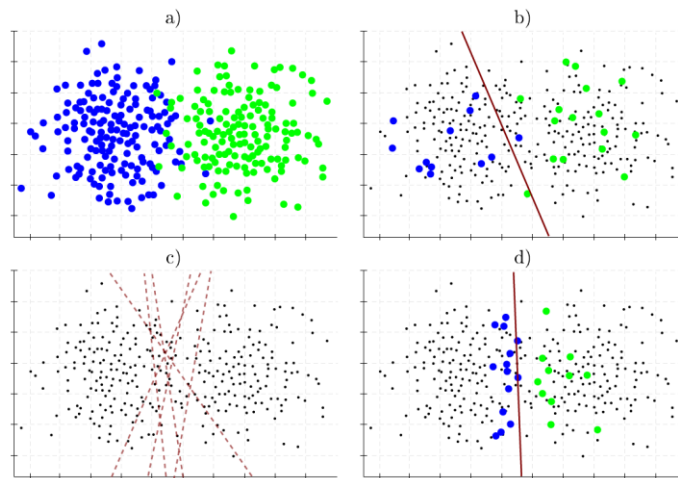


Figure 2: Illustration of QbC sampling a) Original data; b) Decision boundary based on original data; c) Members of the committee; d) The new decision boundary based on uncertain samples

As seen in Figure 2., the QbC samples examples with low confidence and inserts them into the Universum set. The QbC algorithm first constructs a collection (Committee) of sub-classifiers created from a fraction of original data. Then these sub-classifiers vote on generated Universum examples and examples with a highest number of disagreements are selected. After this improvement, the performance of the algorithm improved significantly, as you can see in Table 1.

Once we have obtained the Universum examples, we need to formulate the objective function. As mentioned earlier, Universum learning assumes that the decision boundary is close to uncertain examples. This gives a criterion which needs to be included in the cost function. In the case of SVM classifier then the cost function is:

$$\frac{1}{2} \|w\|_2^2 + C \sum_{i=1}^M \varphi[y_i f_{w,b}(x_i)] + D \sum_{j=1}^N \rho[f_{w,b}(u_j)] \quad (2)$$

where φ and ρ are loss functions, $f_{w,b}$ is the discriminant function with parameters w and b for training points $\{x_i, y_i\}$ and Universum points $\{u_j\}$ with free parameters C and D . The Universum was used also in combination with Boosting (AdaBoost) algorithm (with hypothesis F and L1 regularization where D controls the weight) and in that case the cost function is:

$$\min_w \frac{1}{M} \sum_{i=1}^M \exp(-y_i F(x_i)) + \frac{C}{2N} \sum_{j=1}^N F(u_j)^2 + D 1^T w ; s. t. w \geq 0 \quad (3)$$

Once training is done, during the inference process is standard as for any regular SVM classifier.

As a part of our future work, we would like to explore the possibility of a “close miss” Universum data. Especially in cases like signature verification, where forgery is common. We would expect the forged examples to be quite close to the decision boundary. If we have a label for forged examples, we would like to have them the “forged” label, but at the same time be close to the decision boundary.

3. Experiments and Results

We have evaluated our method to the baseline method presented in (Griechisch et al., 2013), where we used the same evaluation protocol. The method of (Griechisch et al., 2013) achieves good results on the dataset, (composed of 300 signatures from 10 authors) but our technique could outperform it. At the same time we used a toy dataset to visualize the influence of Universum learning on a small dataset and as you can see in Figure 3, the decision boundary is much more viable and is much less overfitting than in case without Universum examples.

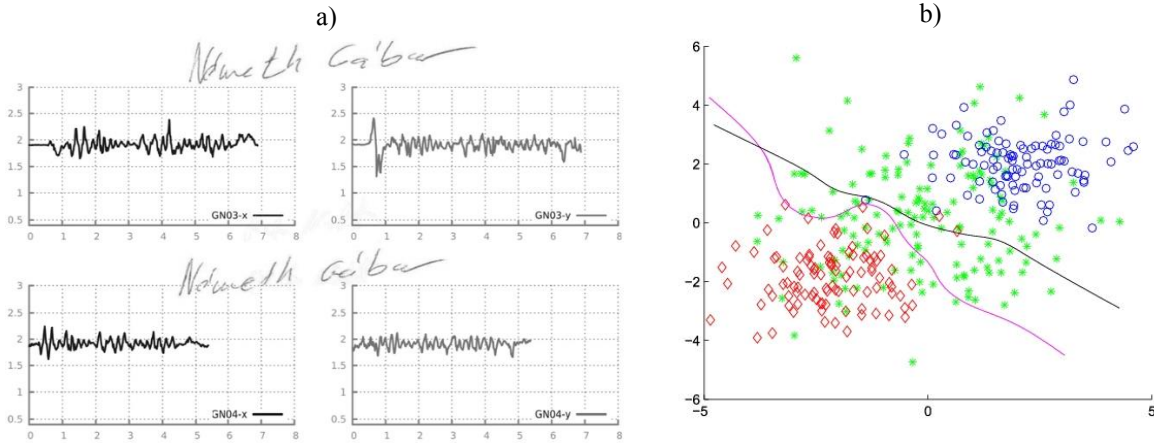


Figure 3: a) Examples from the dataset and qualitative results of the Universum learning b) [(pink) original classifier (black) classifier with Universum data]

Table 1: Performance of classifiers on Accelerometer and Gyroscope data

Method → Dataset ↓	baseline	USVM	USVM + Hermite	USVM + QbC	USVM + Hermite + QbC
AccSig	88.00	90.72	91.25	92.46	92.89
GyroSig	80.44	83.96	84.61	85.88	86.02

The qualitative results are presented in Figure 3 and the quantitative results are evaluated in Table 1. In both cases, we can see the improvement achieved thanks to Universum learning. Our method was able to improve

by 4.89% / 5.58% the baseline method due to various factors. If we considered each of the improvements separately, then the gain was as following: Hermite polynomial approximation: 0.53% / 0.65%, Universum Learning 2.72% / 3.46%, QbC sample selection for Universum learning 1.74% / 1.92 %. As we can see the combined approach is higher than any of the individual approaches, but the final gain does not add to the sum of partial gains, what could be expectable, since some of the gains could actually overlap for different partial methods.

4. Conclusion, Discussion and Future Work

In this paper, we have presented a novel use of the Universum learning on task of classification of signatures from accelerometer and gyroscope data. At the same time, we introduced a novel approach for selection of Universum examples which outperforms the random averaging used in previous Universum learning classifiers. At last we also presented a novel approach for feature selection based on Hermite polynomials, which improves the performance of baseline technique which used the Legendre polynomial approximation. In the end we can conclude that our solution was able to outperform the baseline technique by 4.89% / 5.58% and that the combination of Universum learning, our new sample selection method, and the new features proves to be an efficient combination.

Also, as we can see, the concept of Universum learning is highly dependent on Universum set. The generation of this set still does not fully capture the uncertainty in examples and needs to be tuned and designed in task-specific manner. This is a topic which we would like to address in our future work. Especially we would like to build a model which can produce unlikely examples before the approximation happens. For this, we need to build a meaningful representation of the signatures themselves, such that the final result will be hard to classify even by human evaluators. Some of the methods which we would like to explore in this manner are generative density models. The authors would like to thank to SSHRC Canada and NSERC Canada for their financial support.

References

- Baron, R., & Plamondon, R. (1989). Acceleration measurement with an instrumented pen for signature verification and handwriting analysis. *IEEE Transactions on Instrumentation and Measurement*, 38(6), 1132–1138.
- Bunke, H., Csirik, J., Gingsl, Z., & Griechisch, E. (2011). Online signature verification method based on the acceleration signals of handwriting samples. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)* (Vol. 7042 LNCS, pp. 499–506).
- Cherkassky, V., Dhar, S., & Dai, W. (2011). Practical conditions for effectiveness of the universum learning. *IEEE Transactions on Neural Networks*, 22(8), 1241–1255.
- Dhar, S. (2014). Analysis and Extensions of Universum Learning. (pp. 37-116)
- Griechisch, E., Malk, M. I., & Liwicki, M. (2013). Online signature analysis based on accelerometric and gyroscopic pens and legendre series. In *Proceedings of the International Conference on Document Analysis and Recognition, ICDAR*
- Impedovo, D., & Pirlo, G. (2008). Automatic Signature Verification: The State of the Art. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 38(5), 609–635.
- Malik, M. I., Ahmed, S., Dengel, A., & Liwicki, M. (2012). A signature verification framework for digital pen applications. In *Proceedings - 10th IAPR International Workshop on Document Analysis Systems, DAS 2012* (pp. 419–423).
- Mautner, P., Rohlik, O., Matousek, V., & Kempf, J. (2002). Signature verification using ART-2 neural network. *Proceedings of the 9th International Conference on Neural Information Processing, 2002. ICONIP '02.*, 2, 636–639.
- Parodi, M., Gómez, J. C., & Liwicki, M. (2012). Online signature verification based on legendre series representation. Robustness assessment of different feature combinations. In *Proceedings - International Workshop on Frontiers in Handwriting Recognition, IWFHR* (pp. 379–384).
- Plamondon, R., & Parizeau, M. (1988). Signature verification from position, velocity and acceleration signals: a comparative study. In *Pattern Recognition, 1988., 9th International Conference on* (pp. 260–265 vol.1).
- Rohlik, O., Mautner, P., & Matousek, V. (2001). A new approach to signature verification: digital data acquisition pen. *Neural Networks, IEEE Transactions on*, 2000.
- Settles, B. (2010). Active learning literature survey. University of Wisconsin, Madison.
- Seung, H., Opper, M., & Sompolinsky, H. (1992). Query by committee. *Proceedings of the Fifth Annual Workshop on Computational Learning Theory*, 287–294.
- Shastri, A., Burchfield, R., & Venkatesan, S. (2011). Dynamic Signature Verification Using Embedded Sensors. 2011 International Conference on Body Sensor Networks, 168–173.
- Sinz, F., Chappelle, O., Agarwal, A., & Schölkopf, B. (2008). An Analysis of Inference with the Universum. In *Advances in Neural Information Processing Systems 20* (pp. 1–8).
- Smart, B., Device, P., Bashir, M., Scharfenberg, G., & Kempf, J. (n.d.). Person Authentication by Handwriting in air using a 2 Biometric Smart Pen Device for Data Acquisition, 219–226.
- Weiping, H., Xiufen, Y., & Kejun, W. (2004). A Survey of Off-line Signature Verification. *International Conference on Intelligent Mechatronics and Automation*, (August), 536–541.
- Weston, J., Collobert, R., & Sinz, F. (2006). Inference with the universum. *Proceedings of the 23rd International Conference on Machine Learning*, 1009–1016.
- Wu, Q. Z., Jou, I. C., & Lee, S. Y. (1997). On-line signature verification using LPC cepstrum and neural networks. *IEEE Transactions on Systems, Man, and Cybernetics. Part B, Cybernetics : A Publication of the IEEE Systems, Man, and Cybernetics Society*, 27, 148–153.