Handwriting Analysis with Online Fuzzy Models

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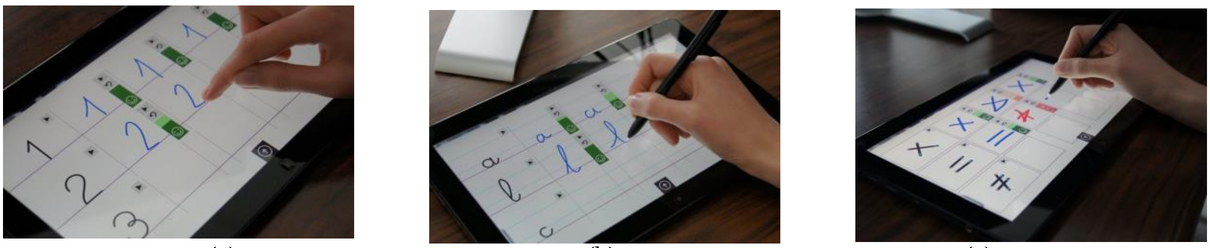
Abstract. This paper presents the early work, done in the context of the IntuiScript project, on handwriting quality analysis. This IntuiScript project aims at developing a digital workbook to help with teaching children how to handwrite. To do so, we must be able to analyse their handwriting, to evaluate 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.



(a) (b) (c)

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.

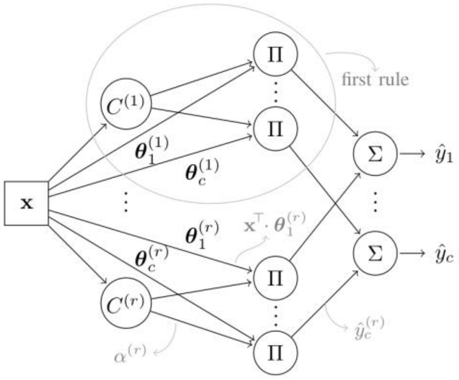


Figure 2: The fuzzy analysis system displayed as a neural network.

A fuzzy inference system is a set a 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 ($\theta_i^{(j)}$) of the input (x) that give membership degrees to all classes (y_1, ..., 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.

$$\text{relative\_confidence}(x^{(k)}) = (y^{(k)} - \max(y^{(p)}, p<>k)) / \max(y^{(p)}, p<>k) \quad (2)$$

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 asses 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.

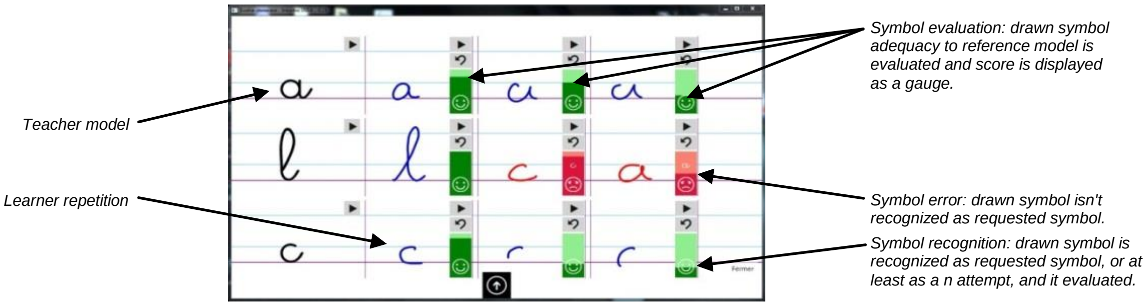


Figure 3: Global analysis score (using HBF49 only).

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.

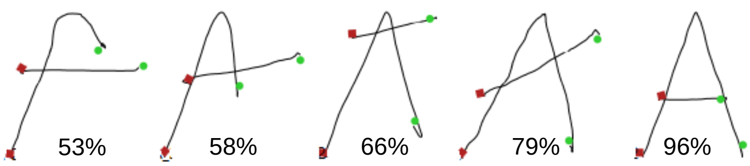


Figure 4: Confidence values for FS 1 (shape) for some 'A' samples.

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

Delaye, 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