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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; Djioua 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

$$S = \{S_1, S_2, \ldots, S_n, \ldots, S_N\} \tag{1}$$

be a set of N genuine signatures. In this paper, each signature S_n is considered as a sequence of elements $S_n = (z^1_n, z^2_n, \ldots, z^i_n, \ldots, z^I_n)$, where each element z^i_n is a 4-tuple $z^i_n = (x^i_n, y^i_n, t^i_n, p^i_n)$, with: - x^i_n and y^i_n : coordinates of the pen on the writing plane; - t^i_n : timestamp; - p^i_n : 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,....,M-1
- $s^M = s^{M-1}$

2) Velocity (v)

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

3) Acceleration (a)

- $a^i = \dfrac{v^i}{(t^{i+1} - t^i)}$,   i=1,2,....,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

$$S_n = (z^1_n, z^2_n, \ldots, z^i_n, \ldots, z^I_n) \tag{2}$$

where each element z^i_n is a 3-tuple (v^i_n, a^i_n, p^i_n), with: - v^i_n : velocity; - a^i_n : acceleration; - p^i_n : 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):

$$W(S_r, S_t) = c_1, c_2, \ldots, c_K, \tag{3}$$

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 $d(c_k) = d(z^{i_k}_r, z^{j_k}_t)$ between points of S_r and S_t, we can associate to $W(S_r, S_t)$ the dissimilarity measure

$$D_{W(S_r, S_t)} = \sum_{k=1}^{K} d(c_k). \tag{4}$$

2

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

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

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) $\forall\, \bar{p} = 1,..,M$, $\bar{p} \neq p$, yields: $z^{\bar{p}}_r$ is not coupled with z^q_t;

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

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):

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

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

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

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

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

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

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

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, $S_3,\ldots,S_{11}$ for computing stability) and 10 forgeries (10 counterfeit signatures S_2, $S_3,\ldots,S_{11}$ 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→low stability regions; yellow→medium stability regions; red→high stability regions.
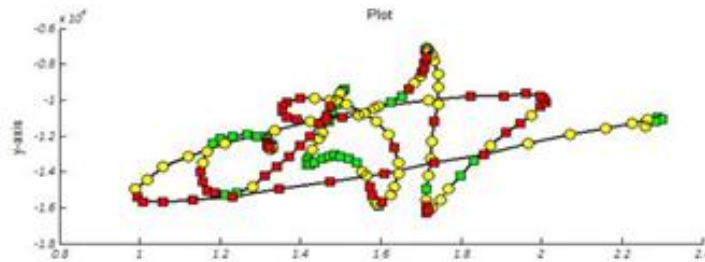

Figure 1. Levels of stability/complexity .

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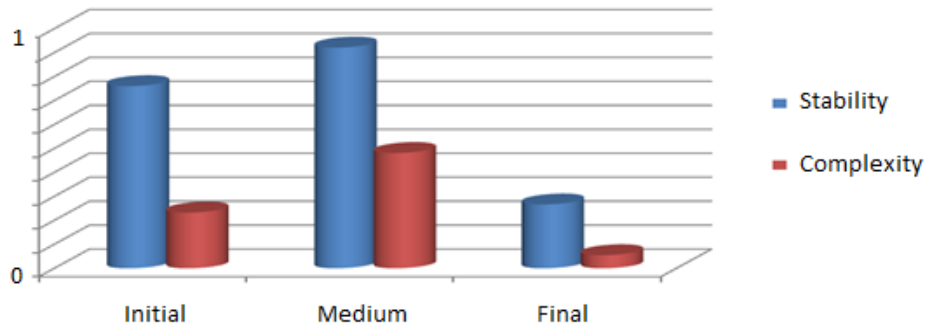
Figure 2. Stability/complexity in dynamic signatures: a regional analysis.

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.

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