Modeling Stability in On-line Signatures

Antonio Parziale[1], Salvatore G. Fuschetto[1] and Angelo Marcelli[1]

Abstract. *A novel definition of stability regions and a new method for detecting them from on-line signatures is introduced in this paper. Building upon handwriting generation and motor control studies, the stability regions is defined as the longest similar sequences of strokes between a pair of genuine signatures. The stability regions are then used to select the most stable signatures, as well as to estimate the extent to which these stability regions are encountered in both genuine and simulated (forged) signatures, thus modeling the signing habit of a subject. Experimental results on the SUSig database show that the proposed model can be effectively used for signature verification.*

Reference: Antonio Parziale, Salvatore G. Fuschetto, Angelo Marcelli (2014). Modeling Stability in On-Line Signatures. J. Forensic Document Examination, Vol. 24, pp. 37- 45.

Keywords: Signature verification, Stability, Handwriting generation.

1. Introduction

Handwritten signatures are one of the most interesting biometric features since people are familiar with the use of signatures in their daily life, and they are largely accepted as proof of one's individual identity. In recent years, along with the extraordinary diffusion of the Internet and the growing need for personal verification, automatic signature verification is being considered with renewed interest.

Handwritten signatures are complex patterns that originate from a complex generation process that depends on both the psychophysical state of the subject and the writing conditions. Hence, a large amount of variability can be observed in the handwritten signatures of a subject produced at different times (Impedovo & Pirlo 2008; Impedovo & al., 2012). Still, the signature is a highly automated motor task that the writer has learned along the years, and therefore, it has been stored in his/her brain as both a sequence of target points to reach and a sequence of motor commands to be executed (Senatore, 2012). So, it is expected that variations in the signing conditions mentioned above may affect some of the signature features, but not all of them. Therefore, it is not surprising that many efforts of the scientific community have been carried out so far for the analysis of signature stability, under the assumption that the stability regions of a signature convey useful information for automatic signature verification.

Signature stability can be estimated directly from the signature signal or indirectly on the set of features used for representing the signature (Impedovo & Pirlo 2008). Among the methods for directly estimating on-line signature stability, those using Dynamic Time Warping (DTW) to derive a local stability function (Dimauro & al., 2002; Huang & Yan, 2003) are the most similar to the one presented in this paper in that the analysis of local stability is used to select the best subset of reference signatures (Di Lecce & al., 1999). These approaches have shown that there is a set of features that remains stable over long periods, while there are other features that change significantly with time, as a function of signer age (Guest, 2004: Guest, 2006; Kato & al., 2006; Houmani & al., 2009). Signature variability is affected more by fluctuations of the parameters associated with the central neural coding than the peripheral parameters reflecting the timing properties of the muscular system activated by the action plan (Djioua & Plamondon, 2009).

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Building on those findings, we propose a method for modeling the signing habit of a subject by detecting the stability regions in a set of genuine signatures. The model builds upon handwriting generation studies and is provided in terms of both the most representative signatures and an estimate of their variability. In the following, Section 2 presents the rationale of the method, while Section 3 describes its current implementation. Section 4 reports the results of a signature verification experiment, while the conclusions summarize the most important findings and outline future work.

2. The rationale of the method

According to handwriting generation studies, the complex movements needed to generate handwriting can be seen as a composition of elementary movements, each corresponding to an elementary shape or stroke (Plamondon & al., 1989). Such elementary strokes are drawn one after the other and the fluency in writing emerges from the time superimposition of the strokes. In other words, as the writer becomes familiar with a given word, he knows how long it takes to draw a stroke and where it will finish, so that the next stroke can be initiated before the current one is completed (Plamondon, 1995). As a consequence, group of strokes with which the writer is familiar with are "embedded" into a single sequence, which is drawn without any feedback, as they were "elementary" writing movements.

Studies on motor control have proven that at the beginning of handwriting learning, each stroke is aimed at reaching the target point that has been visually selected and is executed independently from the previous or the following one. Such a stop-and-go writing modality is slow, because after reaching a target point the next one needs to be selected and the appropriate motor commands planned, and expensive, because of both the cognitive load for planning and the need to overcome the inertia for executing each stroke. By repeated practice, the sequence of target points becomes familiar to the writer, as well as the sequence of motor commands needed to execute them, so that the next movement can start before the current one terminates. This anticipation allows for a faster and more economical writing, because of the elimination of both the pauses between successive strokes and the corresponding inertias. When the learning completes, fluency is achieved, in that the whole sequence of motor commands has been learned and stored in such a way that it is resorted from memory and the corresponding movements executed automatically with proper timing and without any visual and proprioceptive feedback, as it were an elementary movement (Grossberg & Paine, 2000; Senatore, 2012).

According to those findings, and because in case of a highly automated handwriting movement as a signature its central neural coding is less prone to variations than the peripheral parameters reflecting the timing properties of the muscular system activated by the action plan, we assume that sequence of strokes corresponding to well learned movements will appear in many instances of a signature. Therefore, such sequences of strokes represent the desired stability regions, that together with the estimate of the their variability represent the proposed model of the signer.

3. The proposed method

According to the points raised before, we need to find the target points visually selected by the writer for describing his writing habits, which are hidden in the trace because of the anticipatory effect. For the purpose, any of the stroke segmentation methods proposed in literature can be adopted, and in the current implementation we have used the multiresolution algorithm described by (De Stefano & al, 2004). In Figure 1, the results of the stroke segmentation for both a genuine and a forged signature are shown.

The detection of the stability regions is achieved by an ink matcher that finds the longest common sequences of strokes with similar shapes between the inks of a pair of signatures. For deciding when two sequences are similar enough, i.e. when they match, and in analogy with the stroke segmentation algorithm mentioned above, we exploit the concept of saliency that has been proposed to account for attentional gaze shift in primate visual system (Itti & al, 1998). The rationale behind this choice is that, by evaluating the similarity at different scales and then combining this information across the scales, sequence of strokes that are "globally" more similar than other will stand out in the saliency map. The "global" nature of the saliency guarantees that its map provides more

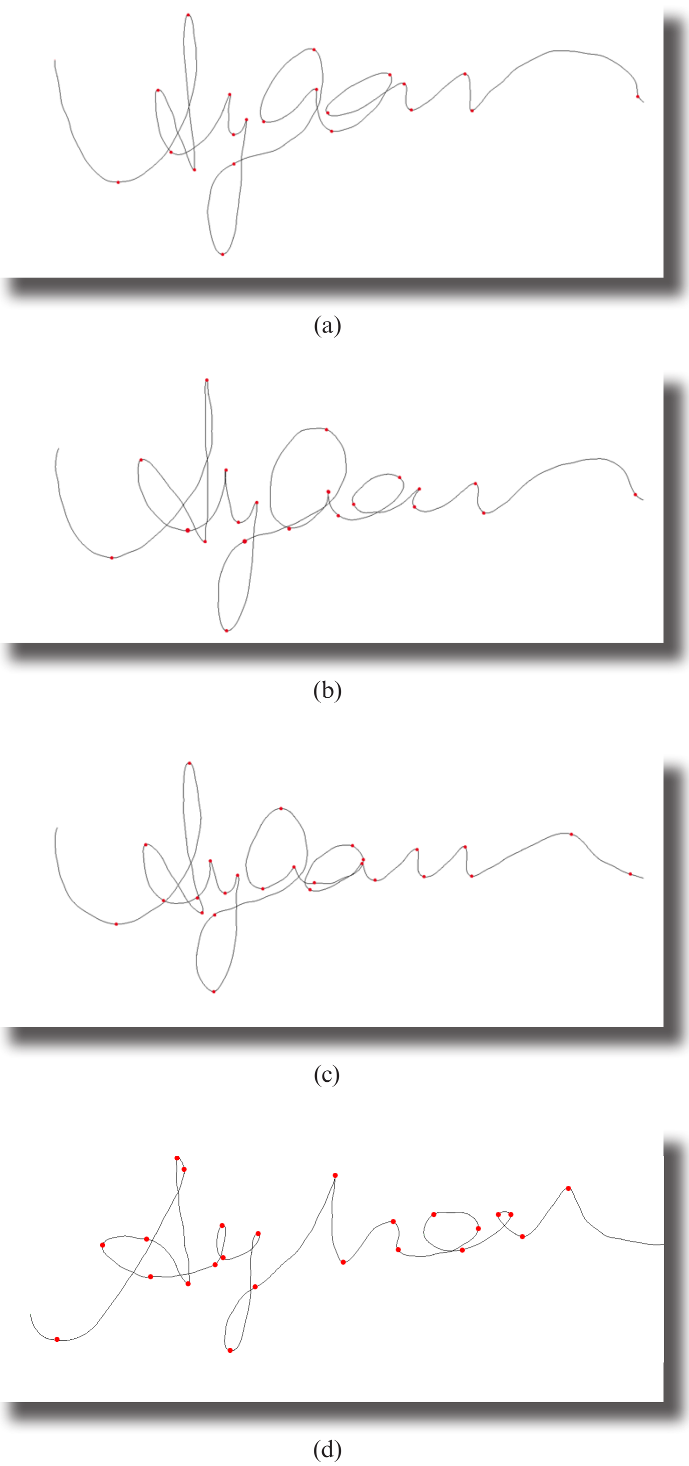


Figure 1: (a) (b) (c) are three genuine signatures extracted by the SUSig database. Signatures (a) and (b) had been selected as reference signature, whereas (c) as a questioned signature. (d) is a skilled forged signature. The segmentation points are in red. Both signature (a) and signature (b) are divided in 22 stroke, whereas (c) is divided in 27 stroke and (d) is divided in 25 stroke.

reliable estimation of ink similarity with respect to that provided by "local" criteria, as it is usually proposed in the literature.

To implement such an approach we need to define a scale space, find a similarity measure to be adopted at each scale, compute the saliency map, and eventually select the matching pieces of ink. As with regards to the scale space, we will adopt as a scale the number of strokes in the sequences whose similarity is being measured. Such a number will be referred in the following as the *length* of the sequence. Let us assume that the two sequences have N and M strokes, respectively. The number of scales corresponds to the length $K \leq \min(N,M)$ of the longest similar sequence of strokes. Note that the inequality sign holds because we assume that ascenders and descenders can match only themselves, not any other strokes. For instance, the shape of both the character "e" and the character "l" could be segmented in two strokes whose shapes could be very similar, but because the former does not include any ascenders, while the contains two of them, such a match is not even attempted. Thus, K represents the length of the longest common sequence of compatible strokes, i.e. strokes that can be matched. Successive scales are obtained considering sequences made of k=K, K-1, …, 2 strokes (De Stefano & al., 2007).

As a similarity measure, we adopted the Weighted Edit Distance *(WED)*, which measures the shape similarity between pair of strokes (De Stefano & al., 2005). The shape similarity of a sequence is obtained by adding the *WED* of its strokes.

After the shape similarity is evaluated at each scale, we compute its saliency as it follows. At each scale k, the most similar pair of sequences is selected and the saliency S_{ij} of all its strokes is computed as $S_{ij} = WED_{ij}/k$. Thus, the saliency map for a pair of inks made of N and M strokes, respectively, assumes the shape of an NxM array, whose elements are either 0, in case of incompatible strokes, or S_{jj}. The saliency map is then thresholded, and the longest diagonal sequences of values S_{ij} greater than the threshold constitute the desired regions of stability.

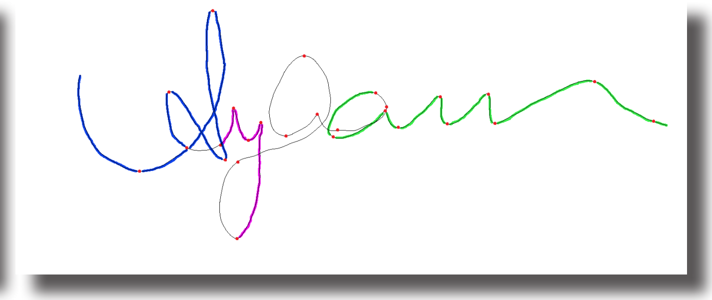
In way of principle, one would expect that, if more than two signatures are available, repeating the processing described above for every pair of signatures will result in the same stability regions. In practice, however, both the stroke segmentation and the ink matching may introduce errors, in locating the

(a)

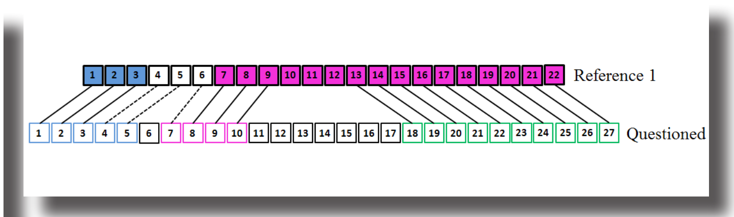
(b)

Figure 2: In blue and magenta are painted the stability regions detected by matching the ink of the reference signatures showed in Figure 1.a and 1.b. The stability regions of both signatures are 19 strokes long

segmentation points and/or in deciding if a sequence of strokes is similar to another that may produce different stability regions for the set of signatures. To reduce such a variability, recalling that the level of automation is the result of the learning process as described above and that learning is an individual feature, we conclude that long stability regions are more writer-specific than short ones, and remove the stability regions found in a pair of signatures that are subsequences of longer ones found in a different pair. If, after this removal, there still are different stability regions found in different pairs of signatures, it is necessary to define a strategy for selecting those genuine signatures, called *references,* that describe at the best the signing habits of the writer and that are the most robust with respect to the variability introduced by our system. In a recent work (Parziale, A., Fuschetto, S.G & Marcelli, A, 2013), we have shown that the best results are obtained by choosing as references the two signatures, ref_1 and ref_2, which minimize the error rate on the training set. Thus, according to our basic assumption, the stability regions between the references, i.e. the longest sequences of elementary movements executed in a highly automated fashion, are represented by the



(a)



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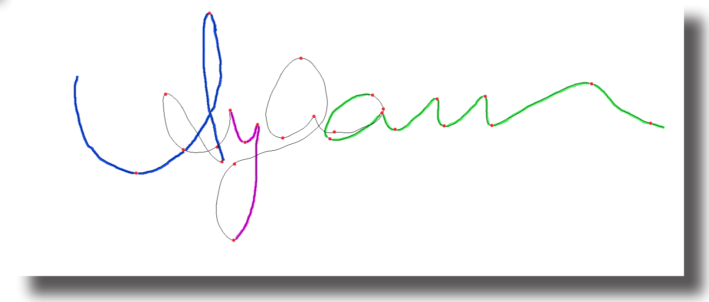


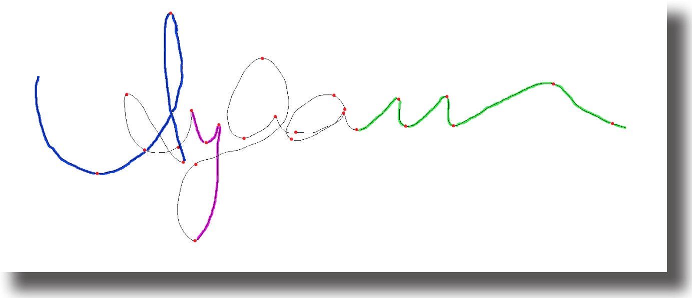
(c)

Figure 3: Questioned 1.c and Reference 1.a are processed by the ink matcher. (a) The longest similar sequence of strokes (LSSS) found by the ink matcher and belonging to 1.c (b) (enlarged image in appendix) Stability regions and LSSS are represented by filled squares and squares with coloured border, respectively. The solid and the dashed lines connect the matching stroke. The dashed lines connect stoke of the LSSS that are not included in the stability regions. The length of the longest common sequence (c) is 16.

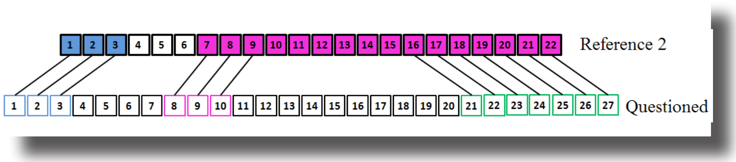
longest sequence of similar strokes (*LSSS*), as shown in Figure 2. The lengths of the stability regions found by matching the references amongst themselves are denoted by $L_s(ref_1)$ and $L_s(ref_2)$, respectively.

Once the references of a writer have been selected, any other signature f, genuine or not, can be mapped in a two dimensional space S by computing its coordinates

$$r_1 = \frac{L_m(f, ref_1)}{L_s(ref_1)} \quad and \quad r_2 = \frac{L_m(f, ref_2)}{L_s(ref_2)} \qquad (1)$$



(a)



(b)

Figure 4: Questioned 1.c and Reference 1.b are processed by the ink matcher. (a) The LSSS found by the ink matcher and belonging to 1.c (b) (enlarged image in appendix) Stability regions and LSSS are represented by filled squares and squares with coloured border, respectively. The solid lines connect the matching stroke. The length of the longest common sequence is 19.

where Lm(f,ref1) and Lm(f,ref2) are the lengths of the LSSS between the reference refi (i=1,2) and f. In Figures 3-6, the longest common sequence of strokes between a questioned signature and a reference is pointed out by solid lines connecting matching strokes.

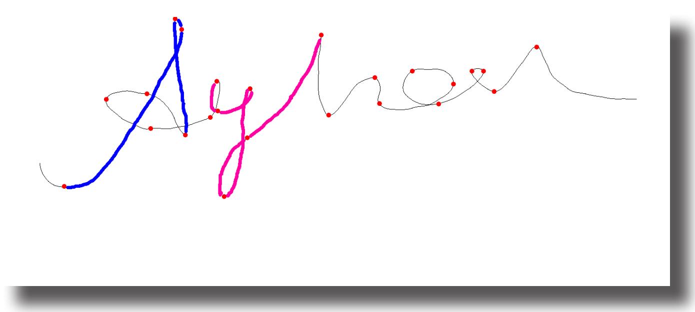
Since r_1 and r_2 vary between 0 and 1, S assumes the shape of a square, whose vertices are (0,0), (0,1), (1,0) and (1,1). In such a space, genuine signatures, that should have a long match with both the references should be represented by points close to the vertex of coordinates (1,1). On the contrary, forged signatures should not have a long match with any of the references, and therefore should be represented by points near to the vertex of coordinates (0,0). In Figures 7 and 8, genuine and forged signatures are mapped in the space *S*.

If a set of genuine and forged signatures for a writer is available, it is possible to select the *references* and to find two regions, C_g and C_f, by mapping the other signatures in the space *S*. C_g is defined as the portion included in S of the circle centered at the point (1,1) with radius T_g equal to the distance of the forged signature nearest to the point (1,1). Instead, C_f is the circle centered at the point (0,0) with radius T_f equal to the distance of the genuine signature nearest to the point (0,0), as shown in figure 8. According to our basic assumptions, thus, the references, with their stability regions, and the two regions, C_g and C_f constitute the *model* of signer we have been looking for.

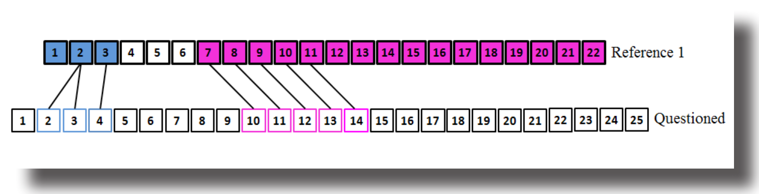
4. Experimental Results

To prove both the validity of our basic assumptions and the efficiency of our implementation of the model, we have performed a verification task by mapping the signatures under investigation in S as above, and by evaluating the position of the points representing the signatures respect to the two regions C_g and C_f. The decision criterion is as it follows:

1. If the regions C_g and C_f overlap, a signature is considered genuine if it belongs to the intersection and it is nearest to T_g than T_f ;
2. If the regions are disjoined or the signature doesn't belongs to the intersection, it is considered genuine if it is mapped in the region Cg or if it is out of C_g but nearest to T_g than T_f.



(a)



(b)

Figure 5: Questioned 1.d and Reference 1.a are processed by the ink matcher. (a) The LSSS found by the ink matcher and belonging to 1.d (b) (enlarged image in appendix) Stability regions and LSSS are represented by filled squares and squares with coloured border, respectively. The solid lines connect the matching stroke. The second stroke of the reference matches with the sequence of the second and the third stroke of the questioned. The length of the longest common sequence is 7.

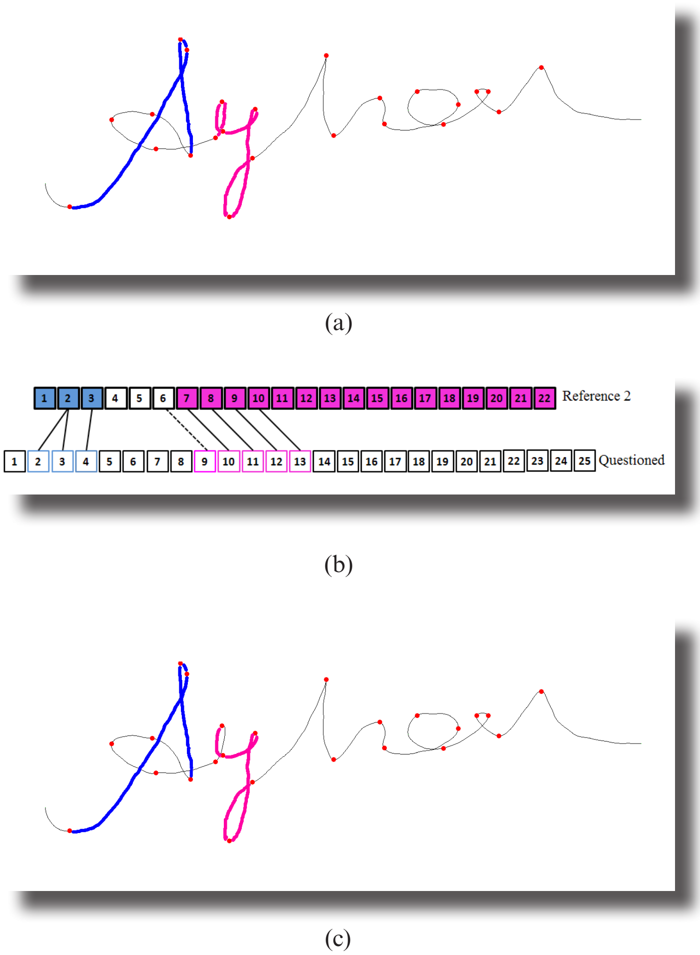


Figure 6: Questioned 1.d and Reference 1.b are processed by the ink matcher. (a) The LSSS found by the ink matcher and belonging to 1.cd (b) (enlarged image in apendix) Stability regions and LSSS are represented by filled squares and squares with coloured border, respectively. The solid and the dashed lines connect the matching stroke. The second stroke of the reference matches with the sequence of the second and the third stroke of the questioned. The dashed lines connect stoke of the LSSS that are not included in the stability regions. The length of the longest common sequence (c) is 6..

We have chosen such a decision criterion because it does not exploit any other information that the length of the match between the questioned and the stability regions of the reference, which, in our model, is an estimate of how much of the automated movements found in the references are found in the questioned: the longer the match, the higher the level of automation of the questioned and, consequently, the higher the likelihood of the questioned to be drawn by the same author of the references. In other words, the adopted decision criterion is meant to estimate the discriminative power of the stability regions

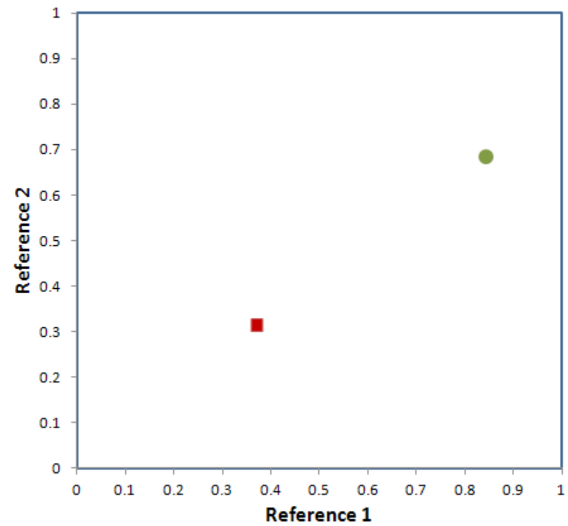


Figure 7: Questioned signatures 1.c and 1.b are mapped in the space S defined by the references 1.a and 1.b. The coordinates of two points follow by the lengths of the longest common sequences and the lengths of the stability regions reported in the captions of the previous figures.

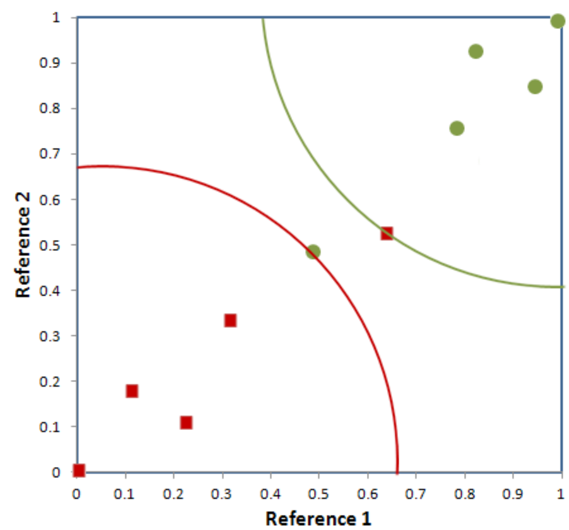


Figure 8: Model of a subject. The mapping of the signatures from the training set and the decision regions for genuine and forgery. The thresholds Tg and Tf are in green and red, respectively.

per se, without relying on any features or classification strategy that could be used to further improve the performance of the system.

The performance of the proposed method has been evaluated on the signatures of the Blind sub corpus of the SUSIG database (Kholmatov, A. & Yanikoglu,

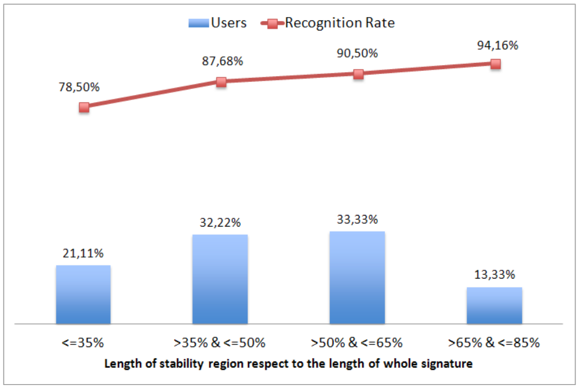


Figure 9: Users of the Blind database are grouped in 4 classes by evaluating the mean ratio between the length of the stability region and the length of the whole reference. In blue, the percentage of users for each class. In red, the mean recognition rate for each class.

B., 2009). The publicly available part of sub corpus consists of signatures donated by 90 individuals with ages varying between 20 and 50 years old. A group of 30 subjects provided eight genuine signatures, while the other subjects provided 10 genuine signatures. Each subject forged the signature of another one 10 times. In our experiments the signatures of each user were randomly divided into two disjoined subsets, the training set, made of five genuine and five forged signatures, and the test set containing the remaining ones. This random partition was repeated three times for each user in order to compute the model of writer in different starting conditions and eventually to show that the results are not biased by the selection of the training set.

Applying the decision criterion described above, we achieved an average recognition rate of 86,7% with a standard deviation of 4,64%, an average False Acceptance Rate of 11,15% and an average False Rejection Rate of 15,28%.

Eventually, for the purpose of showing to what extent the performance of the proposed method are related to the level of automation in the signing process, the users of the Blind sub corpus have been grouped by the mean ratio between the length of the stability region and the length of the whole signature, evaluated over all the pairs of genuine signatures of each user. Users have been grouped in four classes and the recognition rate has been computed for each class, as shown in figure 9. The values of the False Reject Rate and the False Acceptance Rate for each class are reported in Table 1.

5. Conclusions

We have presented a model for describing the signing habit of a subject centered upon the concept of the stability regions of a signature, defined as the longest common sequences of similar strokes among a set of genuine signatures. The adopted definition follows from both handwriting generation and motor control studies, according to which the variability encountered in specimen produced by the same subject at different times is mainly dependent on the actual setting of the parameters characterizing the skeletal muscular system involved in handwriting generation, since the neural central coding of the action plan of the whole signature, that has been developed during the learning, is subject specific and much more stable.

Mean Ratio	Number of Users	Rec. Rate	FAR	FRR
<= 35%	19	78,50%	12,2%	35,4%
>35% & <=50%	29	87,68%	9,1%	15,6%
>50% & <=65%	30	90,50%	6%	14,6%
>65% & <=85%	12	94,16%	3,3%	8,8%

Table 1: Users of the Blind database are grouped in 4 classes by evaluating the mean ratio between the length of the stability region and the length of the whole reference. Mean values of Recognition Rate, FAR and FRR for each class.

The model includes also an estimate of the extent to which the stability regions are found within both genuine and forged signatures.

We have evaluated the effectiveness of the proposed definition of stability by performing a signature verification experiment, in which the stability regions are used for both selecting the references signature and computing the values of two thresholds used to decide whether the signature under verification is genuine or forged. The obtained results on a standard database show that, despite the simplicity of both the feature used to describe the stability region, i.e. its length, and the decision criterion adopted to decide whether an unknown signature is genuine or forged, the performance are comparable with those reported by other authors on the same dataset.

The performance of the proposed method depending on the mean ratio between the length of the stability region and the length of the whole signature brings further evidence for supporting our claim that our definition of stability regions is actually able to discriminate the regions of the signature that capture writer-specific information from those that are more subject to variations depending on the signing conditions. In fact, performance gets better as the stability regions get longer, i.e. as the level of automation in the signing process gets higher, producing more similar ink. On the other side, when the stability region covers a little part of the whole signature it is likely that the user has learned different motor programs for signing and the performance get worse.

The proposed method evaluates only the shape of the signatures. Handwriting generation studies, on the other hand, suggest that, being a signature the result of a dynamic process, a better modeling of the signing habits should also include some information about the dynamics of the process, such as velocity profile, acceleration profiles, total writing time on the paper and on-the-fly movement duration. Those aspects, as well as different criteria to select the references, in particular when different motor programs seems to be performed by the user, a more powerful set of features to describe the stability regions and a more sophisticated decision strategy, will be the focus of our future investigations.

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Appendix

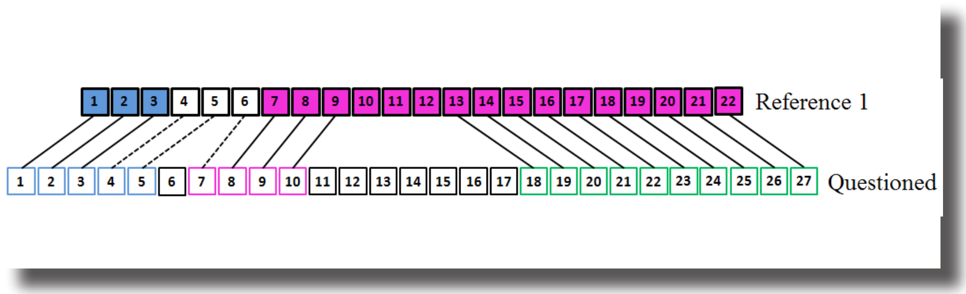
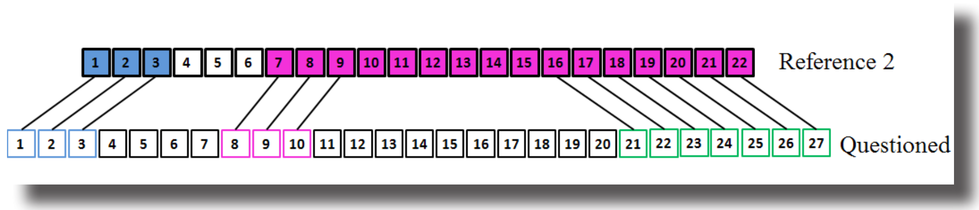


Figure 3: (b) Stability regions and LSSS are represented by filled squares and squares with coloured border, respectively. The solid and the dashed lines connect the matching stroke. The dashed lines connect stoke of the LSSS that are not included in the stability regions. The length of the longest common sequence



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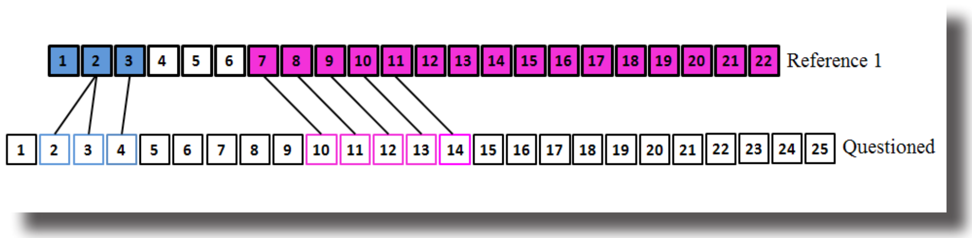

Figure 5: (b) Stability regions and LSSS are represented by filled squares and squares with coloured border, respectively. The solid lines connect the matching stroke. The second stroke of the reference matches with the sequence of the second and the third stroke of the questioned. The length of the longest common sequence is 7.

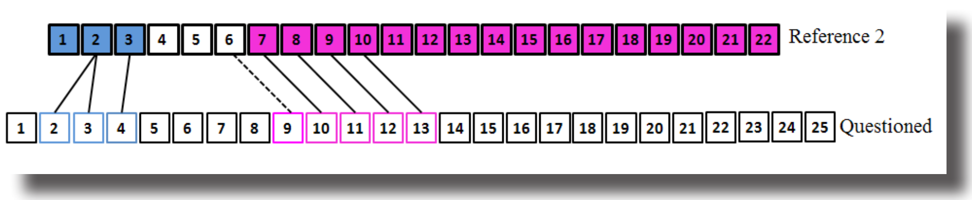

Figure 6: (b) Stability regions and LSSS are represented by filled squares and squares with coloured border, respectively. The solid and the dashed lines connect the matching stroke. The second stroke of the reference matches with the sequence of the second and the third stroke of the questioned. The dashed lines connect stoke of the LSSS that are not included in the stability regions. The length of the longest common sequence