A.Parziale, M. Diaz, M. A. Ferrer, A. Marcelli, *Do synthetic generated signatures reflect the subject motor programs? A pilot study,* Proceedings of 18th IGS Conference, June 2017, Gaeta (ITALY) , pp. 119-122, ISBN: 9788864387062

Do synthetic generated signatures reflect the subject motor programs? A pilot study

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Abstract. Handwritten signature is a biometric trait used for verifying a person's identity. Automatic signature verification systems typically require a lot of specimens in order to model the signing habit of a subject but, in a real scenario, few signature samples are available. To overcome this problem, methods for creating human-like duplicated signatures using one real signature per subject and based on sigma lognormal decomposition have been proposed in literature. In this paper, we evaluate if duplicated signatures show the same amount of variability observed in real signatures by detecting and analysing signature stability regions. In particular, we investigate if real and duplicated signatures could be the instances of a similar motor program. Experimental results on a standard dataset show that in some cases duplication methods introduce a variability that is greater than the writer's variability to such an extent to generate motor programs that do not belong to the writer's repertoire. Results suggest that a connection exists between trajectory plan and motor plan parameters, which cannot be modified independently one from the other in order to generate synthetic signatures that reflect the writer's motor program repertoire.

1. Introduction

Handwritten signature has been used for centuries as a mark for certifying the authorship of documents. At the beginning of the 2000s, laws ratified in many countries around the world established that to sign a document with an online dynamic signature (sometimes referred as electronic signature) has the same legal effect than a static specimen. Since then, research and commercial solutions on automatic signature verification systems are grown with renewed interest (Impedovo & al., 2012).

Two aspects, among many others, make the research on signature verification very engaging: the unexpected intrapersonal variability between different repetitions of a signature and the poor number of signatures available for training an automatic verification system in a real scenario.

Handwritten signatures are the result of a complex generation process that feels the effect of both the psychophysical state of the subject and the writing conditions, so a large amount of variability can be observed between signatures drawn at different times (Impedovo & al., 2008; Diaz & al., 2016b). Nevertheless, a signature is a highly automated motor task learned by the writer 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 & al., 2012), so it is expected that variations in the signing conditions may affect some signature features/regions but not all of them. Many techniques have been presented in literature for the analysis of signature stability and they can be divided in: methods for the stability analysis on raw data (Dimauro & al., 2002; Huang & al., 2003), methods based on motor control studies (Parziale & al, 2014a; Pirlo & al., 2014; Parziale & al., 2015), methods based on set of features extracted from signatures (Lei & al., 2005; Pirlo & al., 2015).

On the other hand, signature verification systems require many signatures for each writer in order to handle with the intra-writer variability and to show good performances. In the last competition on online signature verification, organized in conjunction with the 13th ICDAR conference, 10 signatures were used for training each system (Malik & al., 2015). In a real scenario, it is uncomfortable to obtain many signatures from a subject also because one should collect them in suitable span of time in order to reduce fatigue effects that could arise and introduce additional variability. For this reason, in the last years researchers investigated how to train a verification system using one real signature and a set of synthetic (or duplicated) samples per user. The techniques presented in literature for duplicating a real signature can be divided in: methods based on geometrical distortions (Galbally & al., 2009) or methods based on handwriting generation models (Plamondon & al., 2014; Diaz-Cabrera & al., 2014; Diaz & al, 2016a).

In this paper, we investigate to which extent it is possible to reproduce the intra-writer variability of a subject by using duplication methods that require just one real signature per writer and based on handwriting generation models. The analysis is performed by comparing the stability of the duplicated signatures respect to real genuine signatures using a method inspired by motor control studies. The remaining of the paper is

organized as follow: in Section 2, the methods used for duplicating signatures and for finding stability regions are described, in Section 3 the experimentation is presented while the results are discussed in the conclusions.

2. Method

A signature is a learned movement stored in the brain as a spatial sequence of target points to reach for generating the trajectory (*effector-independent representation*), and as a sequence of motor commands directed to obtain particular muscular contractions and joint movements (*effector-dependent representation*) (Senatore & al., 2012). By repeated practice, a writer learns the repertoire of completely automated movements for executing a particular motor task. An automated movement, or *motor program*, is the ensemble of the sequence of target points to reach, the sequence of motor commands needed to execute the elementary movements (strokes) between each target and, eventually, the proper timing between each command (Marcelli & al., 2013).

Different sources of variability influence the execution of a complex movement, therefore differences can be observed in many replications of a signature. If the entire signature is encoded in a single automated movement, it is expected that its executions repeated in similar writing conditions result in very similar traces. In such a case, in fact, both the effector-independent and the effector-dependent part of the movement are coded by indivisible sequences and the movement execution is robust to both central and peripheral source of variability. On the contrary, if the signature is encoded with more than one motor program, repeated executions may produce different traces because there will be differences in the movements for connecting two consecutive motor programs. In fact, these movements are computed on the fly and are sensitive to the state of the effector and to the writing conditions. It follows that the sequences of strokes produced as a single behaviour are instances of a same motor program and they will appear in many instances of a signature. These sequences of strokes represent the stability region of the signature.

2.1 Stability regions

The stability regions are the longer common sequences of similar strokes found in two signatures, where similar means that they are aimed at reaching the same sequence of target points by following the same path (Parziale & al., 2014). To segment a signature in strokes we need to find the target points visually selected by the writer although most of them are hidden in the trace due to the superimposition process that results in a smooth trajectory. To recover the target points we used the segmentation method described in (De Stefano & al., 2004), which mimics some of the features of the primate visual system. The desired segmentation points are the most salient points of the trace, i.e. those corresponding to the sharpest changes in curvature.

The detection of the stability regions between two signatures exploit the concept of saliency that has been proposed to account for attentional gaze shift in primate visual systems. 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 others will stand out in the saliency map. The similarity of two sequences S_1 and S_2 made up of b strokes is computed as in eq. (1), where W_h measures the shape similarity between 2 strokes by adopting a weighted edit distance while T_h quantifies the similarity between the relative positions of the target points for each pair of strokes (Parziale & al., 2014b). The longer common sequences of strokes with a similarity greater than a threshold are chosen as stability regions.

$$Sim(S_1, S_2) = \sum_{h=0}^{b} W_h * T_h \quad (1)$$

2.2 Signature Duplication

The kinematic theory of rapid human movements (Plamondon, 1995) provides a framework that allows to automatically decompose a signature in a sequence of strokes $\boldsymbol{P} = \{P_1, \dots, P_n\}$ and to reconstruct the trajectory of a signature starting from a sequence of strokes, each of which is represented by six parameters $P_i = \left(D_i, t_{0_i}, \mu_i, \sigma_i, \theta_{s_i}, \theta_{e_i}\right)$ (Djioua, 2009). Sigma-Lognormal representation is at basis of two approaches for generating human-like duplicated signatures from one real signature (Diaz & al., 2016a). The *stroke-wise method* mimics the writer intrapersonal variability by changing the sigma-lognormal parameters of the real signature stroke by stroke. The perturbations applied to each parameter are based on Gaussian noise. The *target-wise method* reproduces the writer variability by modifying the parameters $(D_i, \theta_{s_i}, \theta_{e_i})$ of each stroke through the perturbation of the target points of the real signature action plan according to a cognitive inspired model presented in (Diaz-Cabrera & al., 2014), and by perturbing the parameters $(t_{0_i}, \mu_i, \sigma_i)$ using Gaussian noise.

3. Experimental results

The experimentation was carried out on the BiosecurID Dataset, which contains 16 genuine on-line signatures for each of 132 users. Signatures were collected in four sessions over a six-month period (Galbally & al., 2015). In order to verify that the Sigma-Lognormal model could properly represent these signatures we evaluated the *SNR* value described in (Plamondon & al., 2014), which should be at least equal to 15 dB to obtain a good

reconstruction. The average *SNR* computed over all the signatures of the dataset is equal to 19.91 dB with a standard deviation equal to 2.21, so reconstructed signatures could be used for our purposes.

The first experiment was aimed at identifying the signature that best represents the motor programs repertoire of each writer. As described above, the acquisition of a motor program is the result of the learning process, which is an individual feature and longer sequences of similar strokes between two signatures are instance of a same motor program. Furthermore, the longer are the sequences of similar strokes, the more stable are the signatures and more robust is the motor execution respect to the writer variability. It follows that to identify the most representative signature of a writer we have to find the one respect to which the writer stability is higher. We denoted with $\{G_i^w | \, i = 1, \dots 16, w = 1, \dots, 132\}$ the *i-th* real genuine signature drawn by the *w-th* writer and segmented in $l(G_i^w)$ strokes. Each real genuine signature G_i^w was compared with all the other 15 signatures produced by the same writer; for each pair, we denoted with $ss(G_i^w)_j$ the number of strokes that belong to the stability regions found by comparing G_i^w and G_j^w. To evaluate to which extent G_i^w and G_j^w were encoded by the same motor programs, we computed the ratio $M_{ij}^w = ss(G_i^w)_j / l(G_i^w)$, which varies between 0 (signatures are instances of completely different motor programs) and 1 (signatures are instances of a same motor program). The *i-th* real signature that best represents the writer *w*, from now on denoted with G_{best}^w, is the one with the greater $\overline{M_i^w} = \sum_j^{15} M_{ij}^w / 15$. The average $\overline{M_{best}^w}$, computed by considering the most representative signature G_{best}^w of each writer, is equal to 0.67 and the standard deviation is 0.12.

In a second experiment we synthesized 10 duplicated signatures $\{D_k^w | k = 1, \dots, 10\}$ for each G_{best}^w by adopting once the stroke-wise and then the target-wise method. We investigated to which extent the variability generated by the duplication method was comparable to the writer's variability. We verified if it is possible to reproduce the writer's motor programs repertoire by the duplication of one real genuine signature. For this purpose, we looked for the less stable duplicated signature, i.e. the duplicated signature D_{sm}^w with the smallest number of similar strokes respect to G_{best}^w and, eventually, we evaluated the stability of a writer *w* respect to both D_{sm}^w and G_{best}^w. The rationale is that a duplicated signature is significantly different from the real one it derives from when the variability introduced by the duplication method is so large that the two signatures are executed with a different set of motor programs. On the basis of our definition of stability, if the writer is not stable respect this duplicated signature it means that the duplicated signature is the execution of motor programs that do not belong to writer's repertoire. We compared each duplicated signature D_k^w with the signature G_{best}^w from which it was derived, and the number of strokes $ss(D_k^w)_{best}$ that belong to their stability regions was computed. The less stable duplicated signatures shown an average $ss(D_{sm}^w)_{best} / l(D_{sm}^w)$ equal to 0.24 (standard deviation equal to 0.17) and to 0.38 (standard deviation equal to 0.17) when they were synthesized with the stroke-wise and the target-wise method, respectively.

We evaluated to which extent a signature $\{G_k^w | \, k = 1, \dots 16, k \neq best\}$ had motor programs in common with D_{sm}^w and G_{best}^w by computing the ratios $M_{sm_k}^w = ss(D_{sm}^w)_k / l(D_{sm}^w)$ and $M_{best_k}^w = ss(G_{best}^w)_k / l(G_{best}^w)$, respectively. We defined three levels of stability for a writer: *High*, *Medium* and *Low Stability*. The greater is the number of signatures characterized by long sequences of similar strokes, the more stable is the writer. Therefore, the level of stability of a writer respect to his best genuine (his worse duplicated) is *High* if the majority of G_k^w satisfy the condition $M_{best_k}^w \geq t_H$ ($M_{sm_k}^w \geq t_H$), is *Low* if the majority of G_k^w satisfy the condition $M_{best_k}^w < t_L$ ($M_{sm_k}^w < t_L$), is *Medium* otherwise. In Table 1 it is shown how writers are distributed in each class of stability respect to real and duplicated signatures. The two thresholds t_L and t_H were set equal to 0.3 and 0.6, respectively. The results show that duplicated signatures are less stable than the real ones and that target-wise method produces signatures more stable than the stroke-wise method.

4. Discussions and Conclusions

We investigated the variability introduced by two signature duplication methods based on the kinematic theory of rapid movements. In the light of how brain represents a highly automated learned movement, we argued that a signature is the result of the execution of one or more motor programs whose neural coding is less prone to variations than the peripheral parameters reflecting the properties of the activated muscular system. The state of the effector and the writing conditions could introduce a significant variability between many repetitions of a signature, especially when signatures are coded by more than one motor program. By looking for the longer sequences of similar strokes between two signatures, we can estimate the writer's motor program repertoire and then quantify the level of automation in the motor execution. The results show that 98 over 132 writers are highly stable respect their most representative signature, while the others are medium-stable. By duplicating the most representative signatures, one would expect to produce signatures that are instances of motor programs belonging to the writer's repertoire. Accordingly, one would expect that D_{sm}^w is more similar to those real signatures that have less in common with G_{best}^w. The results show that the majority of writers are weakly stable respect to the D_{sm}^w generated with the stroke-wise method, while are medium-stable respect to those generated

with the target-wise method. It means that duplication methods in some cases introduce a variability that is not comparable with the writer's variability to such an extent to generate motor programs that do not belong to the writer's repertoire. By noting that stroke-wise method perturbs the Sigma-lognormal parameters one independently of the other while the target-wise method, which performs better, introduces a geometrical correlation at least between $(D_i, \theta_{s_i}, \theta_{e_i})$, the results here presented suggest that intra-personal variability that we usually observe derives from an existing correlation between the parameters of each stroke and between the parameters of consecutive strokes. Eventually, from a motor control perspective, it is fundamental to understand how the state of the muscular system is related to the values of some parameters, in particular $(t_{0_i}, \mu_i, \sigma_i)$.

Table 1. Number of writers per class of stability, respect to $\boldsymbol{G^w_{best}}$ and $\boldsymbol{D^w_{sm}}$.

	Real Genuine Signatures	**Stroke-wise method**	**Target-Wise method**
High	98	3	8
Medium	34	28	62
Low	0	101	62

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