Cognitive Inspired Model to Generate Duplicated Static Signature Images

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***Abstract*—The handwriting signature is one of the most popular behavioral biometric traits for person recognition. Such recognition systems capture the personal signing behaviour and its variability based on a limited number of enrolled signatures.**

In this paper a cognitive inspired model based on motor equivalence theory is developed to duplicate off-line signatures from one real on-line seed. This model achieves duplicated signatures with a natural variability. It is validated with an off-line signature verifier based on texture features and a SVM classifier. The results manifest the complementarity of the duplicated signatures and the utility of the model.

***Keywords*-Signature synthesis, Duplicated samples, Signature verification, Biometric recognition**

I. Introduction

Although many efforts are focused on improving the Automatic Signature Verifiers (ASV) in handwriting signatures, nowadays the recognition rates are not competitive for industrial and commercial purposes. It implies that other biometrics have been used in security and safety applications such as the iris, palm-print or fingerprint.

A new effective trends both in static and dynamic signature recognition is the generation of synthetic signatures. Biometric synthetic samples are being a real support to the ASV since they are effective to improve their performances and do not require human donors. Sometimes, donors are not keen on sharing their personal biometric traits because it could compromise the security of their own identities. Even, the acquisition and dissemination of public databases including biometric information raise important legal and security concerns. Moreover, capturing human signature traits involve a large cost in effort and monetary terms. Synthetic signatures appear as a solution to provide large dataset for biometric applications including vulnerability assessment, improving training set on supervised machine learning, performance evaluation, among others.

Generating duplicated synthetic handwriting samples of a person from a limited number of real samples has already been proposed [1], [2]. Focusing on handwriting signatures, different strategies have been used, which can be classified into two approaches:

- *Synthetic generation of new identities.* Recent methodologies have been proposed to synthesize flourish-based signatures with some seldom isolated letters both in on-line [3], [4] and off-line signatures [5].
- *Synthetic generation of duplicated samples.* The synthetic samples are based on real samples. Taking two signatures as seeds, in [6] is developed a method to generate duplicated bitmap images. Authors model the variability of genuine dynamic signatures overlapping two on-line signatures and generating a new specimen between the seeds. The quality of their method is assessed through a commercial verifier converting the samples into off-line image templates. This method was validated showing up that the database with real and synthetic samples achieves similar performance to the database with only real signatures. In dynamic mode, synthetic samples were generated through random distortion using only one signature as seed [7]. In this case, the synthetic samples are used to increase the training set and to improve the performance of the HMM-based signature recognition system. Therefore, techniques related to duplicate samples allow to enlarge the number of samples (both genuine and non-genuine) but not the number of user in a database.

The referenced works related to generation of duplicates are based on geometrical deformations of real signatures with no reference to the cognitive signing procedure [6], [7]. This paper proposes a new model inspired by the cognitive signing procedure to generate duplicated off-line signatures. Our contribution tries to model the signature variability approaching the cognitive and neuromuscular handwriting procedure.

To assess the variability model, as in [7], we will use the duplicated signature samples to increase the training sequence of am ASV. The ASV used is based on texture features and a SVM classifier.

The outline of the paper is organized as follows: The cognitive inspired model to duplicate off-line samples is introduced in Sect. II; Sect. III presents the model implementation; the results with our model is analysed in Sect. IV and finally the conclusions close the paper in Sect. V.

II. Cognitive Inspired Duplication Model

It is well known that the signing procedure involves a high complex fine motor control to generate the signature trajectory with over-learned movements. This procedure is described by the motor equivalence theory which define the

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personal ability to perform the same movement pattern by different muscles.

The motor equivalence theory [8] suggests that the brain stores movements, aimed at performing a single task, in two steps: $i)$ *Effector independent:* In an abstract form, it means the spatial position of each trajectory points for each individual stroke and the relative position among them. As individual stroke we mean a completed drawing line without pen-ups during the hand movement, being the signature build up by a sequence of individual strokes. $ii)$ *Effector dependent:* As a sequence of motor commands directed to obtain particular muscular contractions and articulatory movements.

Although both the *effector independent* and *the effector dependent* are pretty stables, they have a certain degree of variability and they are affected by external inputs and dissonant psychological states. In fact, under pressure, an user usually needs to remember his/her signature before signing producing a signature with a large variability. Similar variability happens with other psychiatric diseases and aging. The muscular path changes due to pose, health, etc., affecting to the signature variability.

Our cognitive equivalence inspired model approaches the *effector independent* signing task as a sequence of point according to observations in a cognitive grid map. It relies on the analysis of the individual strokes, which can be doubly affected as follows: $i)$ An *intra-stroke variability* which is addressed as spatial deformation described by sinusoidal transformation, influencing over the most relevant points of the whole signature. $ii)$ An *inter-stroke variability* approximated by local perturbations of each individual stroke position. The *effector dependent* is considered as general motor commands that the signer try to follow through the cognitive grid map. Inspired by the muscular path reaction, this effect is approximated in our model reconstructing the final ballistic trajectory of the signature. It has been carried out filtering each stroke according to its inertial.

Both effects are not decorrelated. For instance, the signature parts with a denser effector dependent grid will convey a low speed for motor apparatus following such a trajectory. For this reason, the dynamic information could be used to adjust the motor apparatus inertial and should be available to validate the usefulness of the proposed model.

As a lack of the pseudo-dynamic information extracted from static signatures and to carry out the validation of this model, dynamic signatures have been used to test the effectiveness of this model through a realistic conversion into static signatures [9].

III. Generation of Duplicated Signatures

Given the time samples of a real signature trajectory $T[n] = \{x[n], y[n]\}_{n=1}^{N}$, firstly they are scaled at 600 dpi, which is a standard resolution used for static signature database. Then they are 8-connected through Bresenham's line drawing algorithm to produce the signature sequence $T_c[n] = \{x_c[n], y_c[n]\}_{n=1}^{M}$, being M the length of the continuous trajectory, in pixels. The velocity $\{v[n]\}_{n=1}^{N}$, obtained as the derivative of $T[n]$ respect to n is also linearly interpolated to obtain $\{v_c[n]\}_{n=1}^{M}$, representing the velocity of each point in $T_c[n]$. Similar procedure is done with the pressure signal, obtaining $\{p_c[n]\}_{n=1}^{M}$.

The duplicated generation consist in modelling the signature variability divided into six consecutive steps: $A)$ A stroke segmentation to work out with these individual parts of the signatures, $B)$ Selection of relevant points; $C)$ Shape variations according to sinusoidal wave; $D)$ Random variation of the stroke positions; $E)$ Smoothing filter to achieve natural duplicated trajectories and; $F)$ A virtual ink deposition model (IDM) to produce sample as realist as real off-line samples is applied to all reconstructed signature. Fig. 1 summarized the methodology carried out in our approach.

A. Stroke Segmentation

Using the pressure vector $\{p_c[n]\}_{n=1}^{M}$, the stokes are segmented being the pen-ups ($p_c[n] = 0$) as breakpoints. The average velocity of each stroke is worked out as $\{v_{avg}(i)\}_{i=1}^{L}$, being L the number of signature strokes. As the velocity profile can be considered as a linear combination of log-normals [10], the average velocity of individual strokes are worked out as the mean value of the velocity profile peaks. The strokes are classified into three classes: 1) the stroke i is assigned to *"low"* velocity if $v_{avg}(i) \leq 0.6 v_{avg}$, being the v_{avg} the average velocity of all signature; 2) the stroke i is assigned to *"high"* speed if $v_{avg}(i) \geq 1.35 v_{avg}$ and; 3) otherwise the stroke i is considered as *"medium"* velocity. This classification will be useful to define the grid density of perceptual relevant points in order to approach the cognitive map and design the inertial of the filter which approximates the motor apparatus.

B. Perceptual point selection

From a perceptual point of view, it is well known that the corners are the most relevant points [11], although not the only ones in a signature.

The corner points are selected working out the curvature of each pixel which are approached by the radius of its osculating curves [12]. The minimum of the curvature radius are selected as relevant perceptual point.

Extra points are selected among the relevant perceptual point according to stroke classification: for a *low* velocity stroke, we select more points than for *high* velocity stroke which is also related to the human cognitive skills: the slower you write, the more attention is paid to draw the handwriting trajectory. It is accomplished increasing the minimum distance between peaks.

C. Intra-Stroke variability

The variability due to *the cognitive map* is modelled through a sinusoidal transformation applied to the perceptual

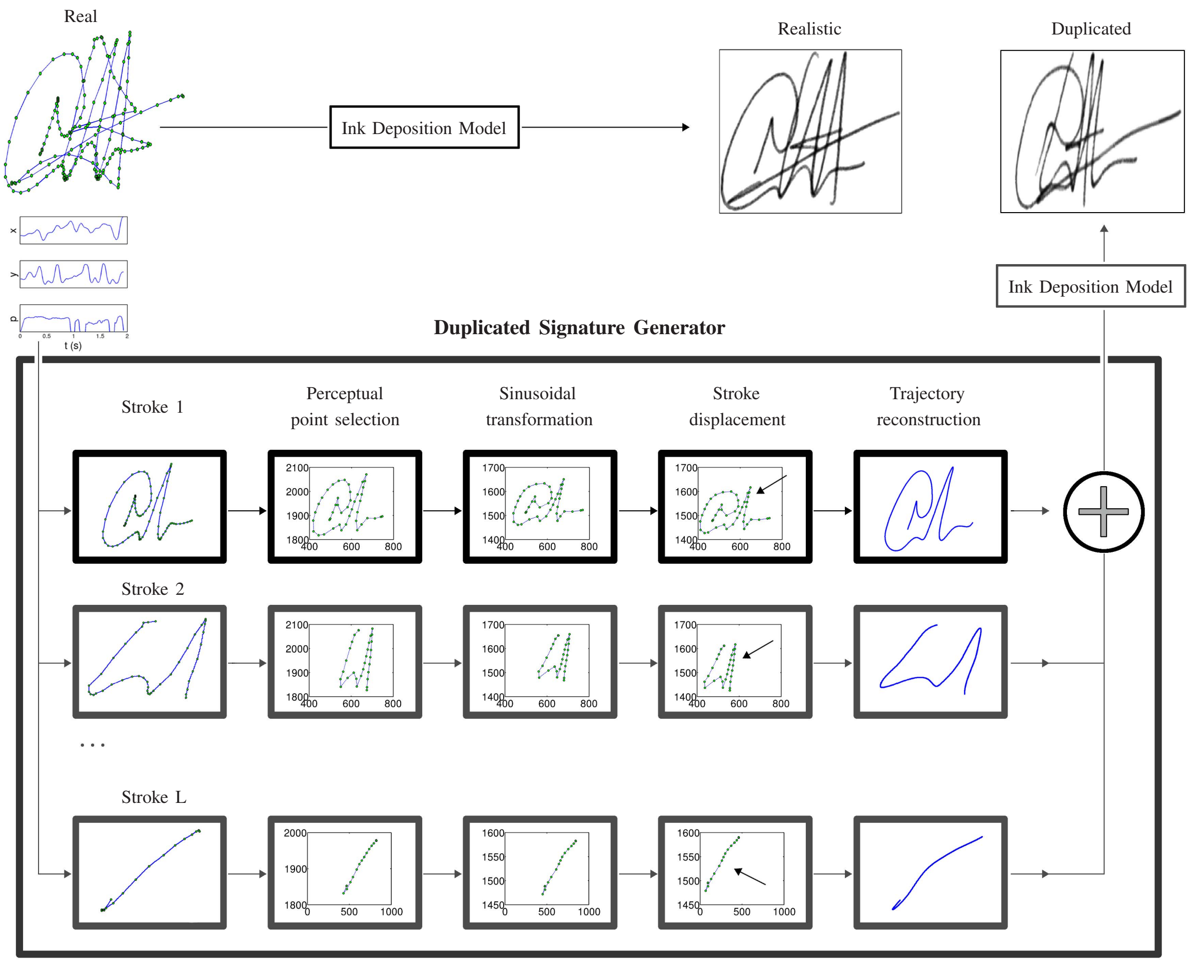

Figure 1: Diagram of the proposed cognitive-based protocol to duplicate signatures.

points of the signature. Sinusoidal transformation allows to approach slight variations in the signer's cognitive map in a practical way. Let $s_p[n] = (\{x_p[n], y_p[n]\})_{n=1}^{P}$ be the sequence of the perceptual points of an individual stroke, being P the number of perceptual point selected, the new sequence is defined as follows:

$$\begin{aligned} x'[n] &= x_p[n] + A_x \sin\left[\frac{2\pi(x_p[n] - \min(x_p[n]))N_x}{h_x}\right] \\ y'[n] &= y_p[n] + A_y \sin\left[\frac{2\pi(y_p[n] - \min(y_p[n]))N_y}{h_y}\right] \end{aligned} \quad (1)$$

Being h_x and h_y the horizontal and vertical sizes respectively measured according to the perceptual point coordinates. The intra-stroke variability for duplicated genuine samples are obtained modifying the amplitudes A_x, A_y and the number of periods N_x, N_y of the sinusoidal waves. These values were randomly selected by a uniform distribution $\mathcal{U}(a, b)$, where (a, b) are the minimum and maximum values, as follows: $A_x = h_x/\mathcal{U}(20,\, 70)$ and $A_y = h_y/\mathcal{U}(20,\, 70)$ for the horizontal and vertical amplitude respectively and for the number of periods: $N_x = \mathcal{U}(0.1,\, 2)$ and $N_y = \mathcal{U}(0.1,\, 2)$. Finally, the new signature trajectory plan is obtained linking the new dots using Bresenham's line.

D. Inter-Stroke variability

The inter-stroke variability originated by the spatial cognitive map variability is approached by a local stroke displacement. Horizontal D_x and vertical D_y position of each stroke are displaced by pseudorandom values drawn from the standard normal distribution $\mathcal{N}(\mu,\, \sigma^2)$. The experimental values are listed as follows.

$$(D_x, D_y) = \begin{cases} (\mathcal{N}(1,\, 4), \mathcal{N}(1,\, 1)) & \text{if } v_{avg}(i) \text{ is } \textit{low} \\ (\mathcal{N}(1,\, 8), \mathcal{N}(5,\, 2)) & \text{if } v_{avg}(i) \text{ is } \textit{medium} \\ (\mathcal{N}(1,\, 12), \mathcal{N}(5,\, 4)) & \text{if } v_{avg}(i) \text{ is } \textit{high} \end{cases} \quad (2)$$

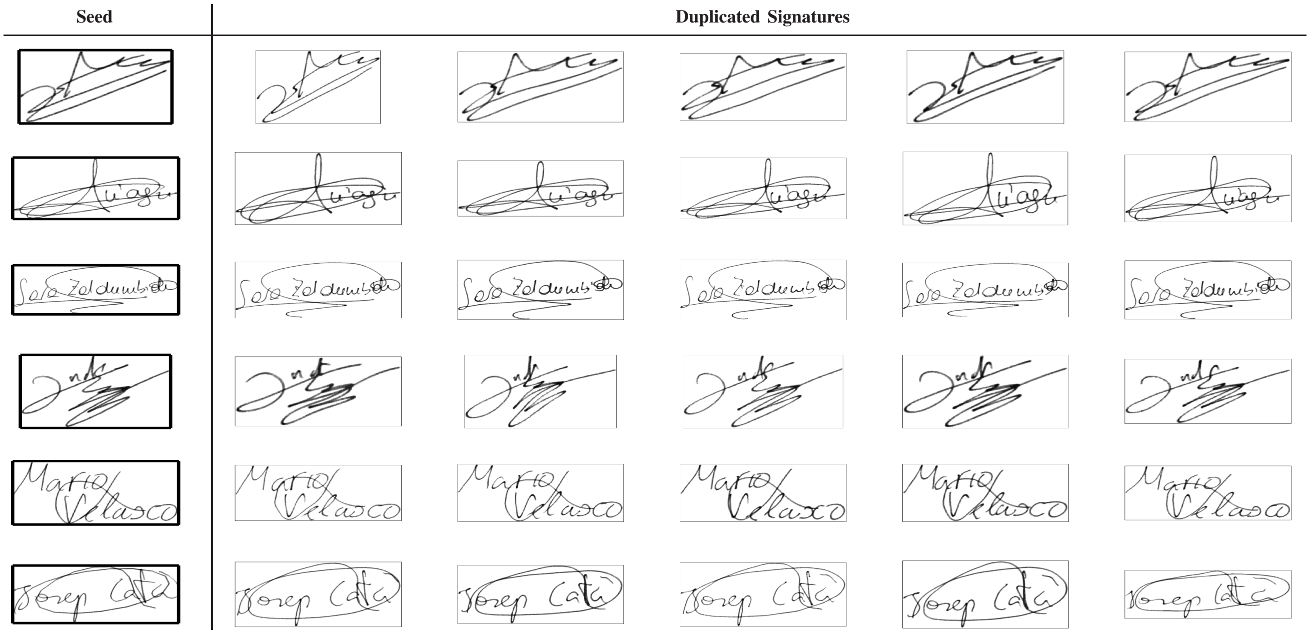

Figure 2: Examples of multiple signatures from only one seed. The first column shown the seed and the rest of columns the duplicated samples.

E. Ballistic trajectory reconstruction

From the above trajectory plan, a filter to emulate the motor system is applied. Since the handwriting trajectories can be approached as polynomial curves, a Savitsky-Golay filter [13] is used to produce human-like trajectory [5] interpolating the trajectory plan point.

The filter works with a frame size f and with the degree k of the polynomial regression on a series of values. Experimentally, the f value is defined by a uniform distribution as $\mathcal{U}(60, 60+10k)$ for each type of stroke and the k value as follows:

$$k = \begin{cases} \mathcal{U}(6,8) & \text{if } v_{avg}(i) \text{ is } \textit{low} \\ \mathcal{U}(4,6) & \text{if } v_{avg}(i) \text{ is } \textit{medium} \\ \mathcal{U}(3,5) & \text{if } v_{avg}(i) \text{ is } \textit{high} \end{cases} \qquad (3)$$

As low velocity trajectories contain more details, they need a higher polynomial degree in order to be reconstructed. For higher velocities, lower polynomial degree is more adequate for smoother curves. *Low* and *high* velocities are generally related to handwriting and flourish respectively. So, all fixed values achieve larger variability in the speedy strokes. It agrees with human behaviour because hand rapid movements are usually less precise than slower ones.

Fig. 3 shows the final trajectory for an individual stroke. We can observe the recovered dots using osculating curves and the final stroke trajectory slightly modified.

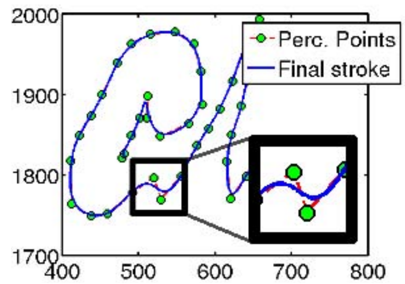

Figure 3: Reconstructed stroke from trajectory plan.

F. Signature Reconstruction and Ink deposition model

At the end of this stage, each stroke is concatenated with the rests of strokes to create the skeletal bitmap image, which represents the skeleton of the signature path. Then, an ink deposition model (IDM) [5], [9] creates realistic synthetic off-line duplicated images. It should be noted that this method is aimed at obtaining realistic images in terms of the stroke texture: several virtual ballpoint are generated following a 2 D Gaussian function as well as modelled inks such as solid, viscous and fluid.

Finally, we could visualize how the variability is modified for a set of samples in Fig. 2. From only one original seed, we show five possible samples synthetically generated through the proposed model.

IV. Model Validation

The experiments have been conducted to analyse whether our cognitive inspired model is able to introduce natural variability using duplicated samples as similar as the variability introduced by human beings. Such a synthetic variability has been tested with an off-line verifier. The validation process tries to determine whether the classifier response is similar in both cases: when real signatures are added to augment the training model or when duplicated ones are introduced. The hypothesis underlying the principle that the duplicated signatures contain complementary information which can be used to outperform the performance of the original models.

A. Database

The dataset used in this trial is the publicly available dynamic MCYT database [14]. It consist of 330 signers including 25 on-line genuine signatures and 25 skilled or *deliberated forgeries*, acquired in a multi-session scenario. Deliberated forgeries mean forged signatures made from certain knowledge of the genuine spatial signature trajectory but it does not necessarily imply acquired skill of a true forger.

B. Verification scheme

The performance evaluation is computed by using the verifier proposed in [15], which is part of the recent state-of-the-art in signature verification. It is based on texture features such as local binary pattern (LBP) and local derivative pattern (LDP). The signature is transformed into the LBP and LDP images which are divided into 12 sectors. The histogram of each sector is worked out, concatenated and its dimension reduced with a Discrete Cosine Transform (DCT) obtaining two separated feature vectors according to LBP and LDP operators. The combination at score level is evaluated through a weighted sum. The classifier is based on a least square support vector machine (LSSVM). [16].

C. MCYT off-line to on-line signature recognition baseline

The baseline is calculated using the dynamic MYCT database converted into realistic off-line images. The evaluation is assessed with four different training models. The first training model is formed by the first 5 signatures; the second with the first 10; the third relies on the first 2 and the last one with the first 4, all according to nomenclature database. While 5 and 10 signatures are traditional enrolment sizes in the literature, 2 signatures is a more challenging scenario with a very limited amount of data. The generation of duplicated data could be exploited in such limited applications. For all cases, the genuine scores were calculated matching the rest of genuine samples of the owners against the trained model. Then, impostor scores were obtained with random selection of genuine samples of others signers not included into the training model. It tries to prove whether a signature without previous knowledge of the originals *(random forgeries)* could be enrolled in the system. *Deliberated forged* scores were calculated against the trained model in each case. Such results are the baseline which estimates the utility and the limits of our duplicated samples, shadowed in Table I.

Table I: Equal Error Rate (EER) results using the texture-based verifier for the two validations. The baselines are shading with certain gray level.

Training		Validation 1	
Real	**Synt.**	**Random Forgeries**	**Deliberated Forgeries**
5	-	1.88 %	19.17 %
10	-	1.07 %	13.13 %
5	5	1.97 %	16.52 %
5	20	1.63 %	16.37 %
5	100	1.43 %	16.19 %
Training		**Validation 2**	
Real	**Synt.**	**Random Forgeries**	**Deliberated Forgeries**
2	-	3.70 %	23.73 %
4	-	2.43 %	18.53 %
2	2	3.33 %	19.86 %
2	8	3.13 %	19.73 %
2	40	2.89 %	19.12 %

D. Evaluating the variability of the duplicated signatures

The aim of this experiment is to ascertain the complementarity between the information of the duplicate samples and the real signatures used to generate them. The training models used to calculate the baseline in the previous section are trained again adding duplicated samples generated from the own real signatures contained in the models. The goal is to determine the ability of the cognitive approach to generate samples with complementary information about the signature owner.

E. Results and discussion

Table I shows the Equal Error Rate obtained using the MCYT signatures (baseline) and the enhanced models trained with real and synthetic signatures.

In general, the results obtained with the duplicate samples outperform the baseline. Such improvement can be observed initially in the deliberated forgeries in which EER starts to decrease, even with the smaller duplicate sets. In the random forgery scenario, the improvements are more observable when larger duplicate sets are included. Although the system generates more synthetic specimens from one signature, the results saturate around 1.5 % for random forgeries and almost 16 % for signatures with previous knowledge. However, obtained results with 10 and 4 real signatures suggests that there is still margin to improve the performance.

The usefulness of the duplicate samples is more evident in the scenario with only 2 training signatures. The cognitive generation approach clearly increases the robustness of the trained models. In the case of the deliberate forgeries, it is possible to improve by 4 % the performance of the original models. As we can observe, the EER saturates at certain number of duplicated signatures. Such saturation is due to the limited inner variability available in only one seed. We could estimate the improvement is higher when we have a few samples in the training model. It might play a special role in criminology and forensic science where they deal with a few genuine samples.

V. Conclusion and future work

A new method inspired by the cognitive neuromotor perspective to generate static duplicated signatures has been proposed. The developed generator introduces non linear deformation in on-line signatures to mimic the characteristics of human beings' variability.

This cognitive method has been validated improving the performance of a recent state-of-the art automatic signature verifier. Database with few genuine samples could find benefits duplicating synthetically their samples following this methodology.

As preliminary evaluation of this model, the validation stage was conducted with dynamic trajectories. However, the duplicated signature method could be adapted for pseudo dynamic features inferring the signature trajectory from off-line signatures. This cognitive inspired model could be used to duplicate dynamic signatures. A painstaking research in velocity profile regeneration may be introduced to the model modifying the original on-line samples.

Additionally, behavioral disorders, neurodegenerative diseases and other cognitive impairment in neurodegenerative problems are related to *muscular path variability*. This approach could be taken into account to generate perturbing trajectories inserting carefully random movements into the inter-stroke variability stage.

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