Abstract—As an emerging issue, multi-script signature verification is a recent challenge for current Automatic Signature Verification (ASV) systems. Relevant differences are presented in the morphology and lexicon of the signature images written in different scripts, such as used symbols, shape of the signatures, legibility, etc. These peculiarities could reduce the success of ASV systems, especially those which were originally designed for only one kind of script. However, one common feature among scripts in ASV is the fact that the greater the number of signatures that are used for training, the better the expected performance. In this work, we propose a method inspired by observations from the neuromotor equivalence theory to artificially enlarge the signature images used to train a state-of-the-art static signature classifier. Experimental results are obtained by using three static signature datasets derived from completely different scripts: Western, Bengali and Devanagari. Our results suggest that the cognitive-inspired model, which aims to duplicate static signatures, tends toward intra-class variability of signatures written in different scripts; the model's beneficial impact is seen in signature verification tests.

I. INTRODUCTION

Static handwritten signatures are supposed to constitute an accepted biometric trait for validating the identity of people in most cultures. Beyond its application in medical tests or graphology assessment, this trait is widely used in legal documents and administration, last wills, financial transfers, etc. Consequently, a lot of attention is paid to static handwritten signatures by industry and forensic and pattern recognition researchers. Although many surveys have manifested much interest in handwritten signatures in recent decades [1], [2], [3], [4], they have nevertheless not yet been exploited to their full potential in automatic verification systems [5], [6], [7]. This is probably due the interesting complications they involve as a result of the behavioral conditions underlying their execution. In fact, two apparently different signatures can be executed by the same writer, while two very similar ones are drafted by two different writers.

Automatic Signature Verification (ASV) systems are frequently focused on single-script\(^1\) conditions, and as a result, using a wide variety of languages constitutes an additional complication to current systems. Although globally many countries have no such requirements in their daily technologies, in multilingual countries such as India, where many popular scripts exist, ASV systems are supposed to work under multi-script conditions. Specifically, in the case of India, Bengali and Devanagari are the most spoken scripts. Indeed, certain steps have been taken in the field of ASV with respect to these scripts specifically [8], [9]. Nevertheless, in this paper, we are more interested in multi-script systems, which have typically been proven through signature identification or verification [10], [11].

With respect to multi-script signature identification, in [12], the identification rates between signatures written in Bengali and Devanagari are studied. The authors obtained promising rates using gradient features followed by an SVM classifier. Another work presented in [13] carried out a comparative examination of the identification of signatures written in Western and Chinese scripts. This latter work supported the findings of the previous one on the use of gradient features for script identification purposes. To distinguish between Bengali and Western scripts, a proposal based on background and foreground information is discussed in [14]. Once again, the power of gradient features is evidenced due to the reported performance. As a further step in this field, [15] highlights the impact on verification when signatures written in Western and Devanagari scripts are identified.

In addition to the interest of multi-script in signature verification, these works also suggest that further attention to multi-script conditions should be warranted. One possibility to improve the current performance on systems in order to discriminate between a genuine and a forged signature is to use as many as reference signatures as possible. However, volunteers are not always willing to share many of their signatures. Beyond the legal conditions due to the data protection law, collecting many repetitions of an individual can be a costly and

\(^1\)The set of letters or characters (i.e. symbols) used for writing a particular language is know as script.
boring process, especially in certain cultures. These drawbacks hinder the application of this technology in a multi-script scenario. To alleviate these drawbacks, the literature proposes to synthesize static handwritten signatures in order to create artificially intra-class variability as a means of enlarging the available specimens, mainly in Western scripts. To that end, two proposals are indicated: the full synthesis of signatures and the signature duplication of real specimens.

The former does not require any knowledge about the signature of a real writer. Instead, from certain rules and criteria, a synthetic signature is defined. For instance, in [16], [17], a static master signature is created first, after which duplicated repetitions of this master signature are performed. Additionally, to complete a realistic scenario in ASV, synthetic forgeries are designed in order to validate the synthetic signature images. The latter procedure uses the real image-based signatures to generate duplicated specimens after certain transformations. Ref. [18] proposes some affine transformations in order to create a meaningful statistical static Western signature database and compare two different classifiers. In [19], a similar work is presented where the authors propose to create artificial genuine and forgery signature images using a set of affine distortions. In order to enlarge the reference signatures, duplicate signatures were generated in [20] through an elastic matching between two almost static reference specimens. In addition to these works, other contributions have taken into account different strategies to generate artificial static signatures from dynamic specimens [21], [22], [23], [24].

In this paper, we use a cognitive-inspired method to duplicate signatures [25]: the method is based on the neuro-motor equivalence theory [26], which studies human action in effector-dependent and effector-independent parts of the signing procedure [27]. The main contribution of this paper consists in assessing the robustness of this novel model to duplicate signatures in ASV against a multi-script scenario. Specifically, we use static signatures from three independent scripts: Western, Bengali and Devenagari. An example of signatures in each script is depicted in Fig. 1. The paper aims to prove the script independence property of this novel cognitive duplication procedure.

The rest of the paper is structured as follows. Section II describes the cognitive-inspired model designed to generate duplicated signatures from off-line ones. Section III describes the datasets used in this work. A performance-based experimentation is given in Section IV, and finally, some conclusions are drawn in Section V.

II. COGNITIVE INSPIRED MODEL TO DUPLICATE STATIC SIGNATURES FROM REAL STATIC SIGNATURES

In this section, we briefly describe the different parts of the duplicator, which is extensively described in [25]. Its design is based on cognitive observations from the equivalence model theory initially formulated by Lashley [28]. The theory is validated in actions undertaken by adult humans, having mature and developed neuromotor systems, and are broken down into both an effector-dependent cognitive and an effector-independent motor level. Both of them require fine motor control and cognitive skills to produce a signature. Although both are quite stable when written by adults, some variability does indeed appear owing to personal characteristics. In this contribution, we have divided these source of variability into three main parts. On the one hand, in the intra-component variability stage, we focus on distortions in the whole signature. On the other hand, inter-component variability is introduced by spatial displacement of non-connected components. Finally, a simple affine transformation is considered to mimic some rotation effects. A previous research work was presented in [23], where some transformations were carried out over dynamic signatures to eventually create realistic static specimens. However, in this work, such a transformation cannot be applied directly as our seed consists of a signature image. Fig. 2 illustrates a general overview of the cognitive-inspired duplicator.

A. Signature Segmentation

The duplicator is initiated with a signature image in gray scale as seed. First, the background of the signature is detected to allow its removal. A simple thresholding operation is thus applied right from the beginning, and then, following the process to eliminate some noise according to [29], the edges of the gray components are smoothed on the image. Next, this step ends up cropping the borders of the image in order to process the minimum canvas size.
\[ \begin{align*} x^* &= x + A_x \sin (\omega_x x + \varphi_x) \\ y^* &= y + A_y \sin (\omega_y y + \varphi_y) \end{align*} \] (1)

For the horizontal component, the parameters of the sine wave are defined as:

- Sinusoidal amplitude: \( A_x = M/\alpha_A \), where \( \alpha_A \) follows a uniform distribution \( U(5, 30) \) and \( M \) represents the number of columns (pixels) of the image.
- Angular frequency: \( \omega_x = 2\pi/\tau_x \)
- Period: \( \tau_x = M/\alpha_P \), where \( \alpha_P \) follows a uniform distribution \( U(0.5, 1) \).
- Phase: \( \varphi_x = 2\pi\alpha_S \), where \( \alpha_S \) follows a uniform distribution \( U(0, 1) \).

To compute the vertical component, identical values are used. At the end of this stage, we obtain the image \( I_S(x^*, y^*) \), which has been distorted to introduce intra-component variability to the signature image.

In our implementation, the sinusoidal transformation determines each pixel which should be used in the image \( I_S(x^*, y^*) \). For instance, for a pixel \( p \) in \( I_S(x^*, y^*) \) which should be filled according to the sinusoidal transformation, we choose the nearest pixel \( q \) in \( I(x, y) \) in order to guarantee the continuity.

C. Component labeling

Although an individual could visually deduce the writing order in which a simple writing was executed, it is unfortunately not always possible in static signatures due to many components being overlapped. Specifically, this phenomenon usually occurs in Western signatures because of the fact that signers tend to sign with their names, followed by a flourish. Flourish is a rapid component, which is often written over names, complicating isolation. In the case of a Devanagari script, many signatures connect all its components with a matra. Matra is a horizontal line at the top of written text, which usually connects the letters of a single word.

Nevertheless, at this stage of the algorithm, we detect the connected components in the image, while searching through all 8 connected areas. This enables the isolation of some inked components, which can then be distorted separately during the following stage. Thus, we could start to work with a set of \( L \) individual images \( \{ I_i(x, y) \}_{i=1}^{L} \) from each labeled component of the image \( I_S(x^*, y^*) \). For simplicity, the implementation of this stage was performed with the \texttt{bwlabel} function in Matlab. Fig. 3 shows a specimen of each script, along with its detected components.

D. Inter-component variability

This variability is associated with the spatial cognitive map and the relationship between inked components. According to suggestions in [27], the inked component variations are mainly affected by modifications on the motor plan, which is supposed to be the late stage in the movement. In this work, we approach it by applying the relative displacement among detected components, which were labeled in the previous stage. As such, we created a new image \( I_{\text{dis}} \) with the horizontal and vertical component displacement, calculated as follows:

\[ I_{\text{dis}}(x, y) = \sum_{i=1}^{L} I_i(x + \delta_{x_i}, y + \delta_{y_i}) \] (2)

The displacements were introduced through pseudorandom values drawn from a Generalized Extreme Value (GEV) distribution. Three parameters were used to characterize the distribution, namely, location, scale and shape distribution parameters, respectively: \texttt{gevrnd([\xi_i, \sigma_i^\alpha, \mu_i^\beta])}. Accordingly, the \( \delta_{x_i} \) and \( \delta_{y_i} \) were defined with the following values:

\[ \delta_{x_i} = \begin{cases} \text{gevrnd}([-0.5, 20, 40]) & \text{if } \Gamma_i < 0.33 \\ \text{gevrnd}([-0.5, 28, 56]) & \text{if } 0.33 \leq \Gamma_i < 0.67 \\ \text{gevrnd}([-0.5, 36, 70]) & \text{if } \Gamma_i \geq 0.67 \end{cases} \] (3)

\[ \delta_{y_i} = \begin{cases} \text{gevrnd}([-0.5, 8, 8]) & \text{if } \Gamma_i < 0.33 \\ \text{gevrnd}([-0.5, 9.6, 9.6]) & \text{if } 0.33 \leq \Gamma_i < 0.67 \\ \text{gevrnd}([-0.5, 12, 12]) & \text{if } \Gamma_i \geq 0.67 \end{cases} \] (4)

where \( \Gamma_i = \gamma_i/\gamma_T \) means the relationship between the number of pixels in each individual component \( \gamma_i \) and the total number of inked pixels \( \gamma_T \).

This deformation implies that two components, which were originally isolated, may be overlapped in the duplicates (an example can be observed in the resultant signature image in Fig. 2). In the final image, the overlapped pixels blend a factor \( \psi = 0.8 \) to mimic the effect of having two inked overlapped traces.

E. Signature Inclination

The skew is a property which introduces some intra-personal variability. In [30], the skew intra-personal variability in Western signatures was studied, and was modeled...
through a GEV distribution with the following values: \( \theta_r = \text{gevrd}\{-0.19, 3.28, -1.30\} \).

In this work, we assume that this function varies the rotation angle of the signature in order to rotate the duplicated signature image in an ascendant or descendent fashion. It could be considered as an affine transformation in which a Matlab function, \text{imrotate}, has been implemented, with \( \theta_r \) being the pseudorandom rotation angles used in the function.

Finally, it is worth pointing out that all parameters chosen in this work were previously adjusted in [25]. Also, while some proposals need a pair of signatures (e.g. [20]), one strong contribution of this cognitive-inspired model is the use of only one real signature to duplicate.

III. MULTI-SCRIPT STATIC SIGNATURE DATASETS

Three static signature datasets were used to validate our method, which includes Western, Bengali and Devanagari scripts:

- **MCYT-75 Static Signature DB** [31]. This dataset includes 75 signers collected at four different Spanish universities. The corpus includes 15 genuine and 15 deliberately forged signatures per user, acquired in two sessions. All the signatures were acquired with the same inking pen and the same paper templates.

- **Bengali-100 Static Signature DB** [32]. This off-line Bengali signature database was recorded in India with 100 users. They signed using paper as the medium for capturing the writing. From each individual, 24 genuine signatures were collected in a single session. To produce the forgeries, the imitators were allowed to practice their forgeries as long as they wished, with

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Script</th>
<th>Users</th>
<th>Reference*</th>
<th>Genuine*</th>
<th>Forgeries*</th>
</tr>
</thead>
<tbody>
<tr>
<td>MCYT-75</td>
<td>Western</td>
<td>75</td>
<td>2 or 5</td>
<td>13 or 10</td>
<td>15</td>
</tr>
<tr>
<td>Bengali-100</td>
<td>Bengali</td>
<td>100</td>
<td>2 or 5</td>
<td>22 or 19</td>
<td>10</td>
</tr>
<tr>
<td>Devanagari-100</td>
<td>Devanagari</td>
<td>100</td>
<td>2 or 5</td>
<td>22 or 19</td>
<td>10</td>
</tr>
</tbody>
</table>

*number of signatures per user

IV. EXPERIMENTAL RESULTS

Experiments were designed to assess whether our cognitive duplicator model is able to generate off-line signatures which introduce natural intra-personal variability in each user. This synthetic variability is studied using a performance-based analysis. Usually, the greater the number of signatures trained, the better the performance obtained. We will therefore evaluate whether the performance of an ASV is improved when duplicated signatures are added for training. Our goal is to prove that the cognitive duplicator can introduce a certain knowledge source into the system, irrespective of the script used.

A. Performance-based Evaluation

The method was validated from a performance-based perspective. Typically, ASV is validated against two kinds of forgeries, namely, the random forgery test and the skilled forgery test. The first one mimics the situation of an impostor trying to falsify the identity of a signer by using his own signature, whereas the second test is focused on signers who have some knowledge about the signature to forge, which is deliberately executed. These scenarios were simulated using an off-line ASV system based on texture features and a SVM. [29].

As reference signatures, we used the first 2 or 5 signatures registered per user in each dataset for training. Then, we
introduced duplicated signatures generated from these 2 or 5 enrolled signatures in order to assess the performance in each case. We expected to improve the performance as the number of duplicated specimens was increased.

For testing purposes, we used the remaining available signatures in each dataset. To calculate the False Rejection Rate (FRR) curves, we used the remaining signatures for each user. Table I indicates the number of available signatures in each dataset per user. For example, for the Bengali-100 Static Signature DB, the FRR is composed of $100 \times 22 = 2200$ or $100 \times 19 = 1900$ scores, accordingly. To mimic the random forgery test, we used the genuine signatures from the other users. For instance, in the case of the Bengali-100 Static Signature DB, the False Acceptance Rate (FAR) is composed of $99 \times 100 = 9900$ signatures, accordingly. In the case of skilled forgery scenario, we used all available skilled forgeries signatures to compute the FAR curves. Once again, for the Bengali-100 Static Signature DB, the total computed scores were: $100 \times 10 = 1000$, according to the last column in Table I. Finally, the results were given in terms of Equal Error Rate (EER) as well as Area Under Curve (AUC) since these represent the operative points where FRR and FAR curves coincide.

B. Discussion

Experimental results are shown in Table II for all datasets, for both forgery tests, and two training conditions with real reference specimens. The baselines - results without using our cognitive duplicator - are highlighted in gray.

On the Bengali-100 Static Signature DB, adding duplicates has by far the greatest (best) impact among all the scripts considered. Once again, better results are obtained with skilled forgeries, where the training composed of 2 and 5 signatures leads to improvement of 5.76 % and 4.12 % of EER, respectively. In this case, the cognitive duplicator seems to expand the improvement margin in the most critical case, with only two real signatures to train.

On the Devanagari-100 Static Signature DB, in both training sets (with 2 or 5 reference signatures), the use of the cognitive model improves the performance in all cases. On the other hand, although the cognitive model does not improve the performance in skilled forgery tests, it was interestingly kept constant. Although this effect was certainly not expected, we still proved the benefit provided by using this model to expand the training set, without any degradation.

As global conclusion of this section, experimental results suggest that this cognitive-inspired model could benefit an generative ASV [29] tested with different scripts. While consistent improvements were not always obtained, relevant advancements are observed in both random and skilled forgeries in general terms. Since achieving the best performance depends on the chosen ASV, we stopped in 20 duplicated per enrolled signature. In this work we were interested in studying the capacity of our model to introduce coherent knowledge (intra-personal variability) by incrementing the number of duplicated specimens as to prove its script-independent robustness. Additionally, it must be considered that the off-line ASV system was not fine-tuned for each dataset. Instead, its original configuration was used in all tests.

V. CONCLUSION

In this paper, we present a method for static signature verification capable of approaching and creating artificial intra-class variability for multi-script static signature databases. The method consists of a cognitive-inspired static signature duplicator based on observations from the neuromotor equivalence theory. This duplicator is able to cope with the generation of off-line artificial signatures from real signature images. Three main sources of distortions were used to modify the original signature: i) an intra-component variability approach using a

<table>
<thead>
<tr>
<th>Training</th>
<th>Random Forgery</th>
<th>Skilled Forgery</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>R</td>
<td>D</td>
</tr>
<tr>
<td>R</td>
<td>D</td>
<td>R</td>
</tr>
<tr>
<td>2</td>
<td>10</td>
<td>1.40 – 99.87</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
<td>1.40 – 99.87</td>
</tr>
<tr>
<td>10</td>
<td>2</td>
<td>0.89 – 99.91</td>
</tr>
<tr>
<td>20</td>
<td>0</td>
<td>0.79 – 99.95</td>
</tr>
</tbody>
</table>

* R means the real enrolled signatures and D/R means the duplicated per real enrolled signature.

TABLE II: Equal Error Rate (first) and Area Under Curve (second) results in % using the texture-based + SVM verifier with the three datasets. The baselines are shadowed in gray.
sinusoidal transformation; ii) an inter-component variability introduced by the spatial variation of non-connected components; and an affine transformation which simulates the skew intra-personal variability.

This method was evaluated using a state-of-the-art static signature verifier without fine-tuning the original configuration. To prove whether this cognitive model tends to be multi-script-independent, a performance-based evaluation was carried out using three different multi-script static signature datasets: Western, Bengali and Devanagari.

Towards a script-independent method, our future work will focus on extending a comprehensive evaluation of the script-independence property. We plan to prove that this system also works for other static signature scripts, such as Chinese, Arabic or Persian, etc. Additionally, more research will be devoted to the cognitive duplicator, introducing more variability. We are keen on creating a generic model capable of being used generically in static automatic signature verification. Finally, a similar study in on-line signature verification will be an interesting further step.

ACKNOWLEDGMENT

We would like to thank Prof. Umapada Pal and Dr. Srikanta Pal of the Indian Statistical Institute, as well as Prof. Michael Blumenstein from University of Technology Sydney, Australia for sharing the Bengali-100 and Devanagari-100 Static Signature DBs. This study was funded by the Spanish government’s MCINN TEC2012-38630-C04-02 research project and European Union FEDER program/funds.

REFERENCES


