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Multiple Generation of Bengali Static Signatures

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***Abstract*—Handwritten signature datasets are really necessary for the purpose of developing and training automatic signature verification systems. It is desired that all samples in a signature dataset should exhibit both inter-personal and intra-personal variability. A possibility to model this reality seems to be obtained through the synthesis of signatures. In this paper we propose a method based on motor equivalence model theory to generate static Bengali signatures. This theory divides the human action to write mainly into cognitive and motor levels. Due to difference between scripts, we have redesigned our previous synthesizer [1], [2], which generates static Western signatures. The experiments assess whether this method can approach the intra and inter-personal variability of the Bengali-100 Static Signature DB from a performance-based validation. The similarities reported in the experimental results proof the ability of the synthesizer to generate signature images in this script.**

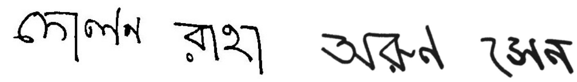
I. Introduction

Beyond a behavioral biometric trait, handwritten signatures can be considered as a human response which expresses personal identity. They are well-accepted in many cultures for legal validation of documents, e.g. last wills or testaments, corporative tax statements, financial transfers and so on. However, the unexpected dissimilarity between two specimens executed by the same signer makes complex and sometimes unpredictable the use of related technology in civil and industrial applications nowadays, especially when many documents require to be automatically processed.

Nevertheless, common benchmarks and competitions are being continuously organized in the most specialized conferences to test the Automatic Signature Verifiers (ASV) designed mainly by industries and academias under the same conditions. Some of the signatures considered in recent competitions in automatic signature verification are executed in several scripts[1] such as Chinese, Dutch, Japanese, Western or Bengali (e.g. [3], [4], [5]).

To test different designed ASVs it is mandatory to use huge number of signatures. In fact, the more signatures, the better the evaluation from a statistical point of view. However, collecting signatures is by far one of the most tedious tasks because of the legal obstacles to make the dataset publicly available. Moreover it is a time consuming and a boring process. These drawbacks are being actively addressed by the use of synthetic signature databases, which is supposed to be one of the recent emerging issue in biometric signatures verification [6]. These databases (of practically infinite size) could be generated using automatic algorithms taking into account a wide variety of realistic factors such as collecting signatures in several sessions; handwriting variations over time or aging effects; simulation of signatures affected by some behavioral disorders, neurodegenerative diseases or other cognitive impairment and so on. In this context, the scientific literature has proposed two ways to synthesize the signatures [7], [8]:

[1]The set of letters or characters (i.e. symbols) used for writing a particular language is know as *script*.



(a) Real Bengali signature (b) Synthetic Bengali signature

Fig. 1: Real and synthetic examples in Bengali script.

1) Generation of duplicated samples. In this case algorithms create artificial intra-personal variability from reference specimens. These reference specimens are the seed of these algorithms. Therefore, they do not create new individuals but possible signatures executed by the signers. Both in on-line [9], [10], [11], [12] and off-line [13], [14], [15], [16], [17], [18], [19], [20], the algorithms are able to generate new samples of a real user. Duplicated signatures present several advantages such as training improvement in ASV, statistically meaningful evaluations, enlarging the number of samples in a database, etc.

2) Generation of new identities. Algorithms are designed in this modality by taking into account different rules and logics in order to simulate realistic effects. In [21] a model is described to generate dynamic signatures based on visual characteristics extracted from the time domain. The method was evaluated from a visual validation. In Galbally et al. [7], [8] the full generation of on-line flourish-based signatures was carried out through two algorithms based on spectral analysis and the kinematic theory of rapid human movements. The first attempt to generate static flourishes in context of static signature image is due to [22]. Two follow-up works were presented in [1], [2] where authors coped with the generation of Western static and dynamic signatures (text and flourish) as well as skilled forgeries under a neuromotor approach.

Although the vast majority of contributions cope with artificially Western signatures generation, the necessity of statistical meaningful databases is found equality in all scripts. Beyond Western signature databases, databases in other scripts such as Arabic [23], Chinese [3], Persian, Russian, Devanagari [24] or Bengali [24] do exists. The lack of enormous databases for

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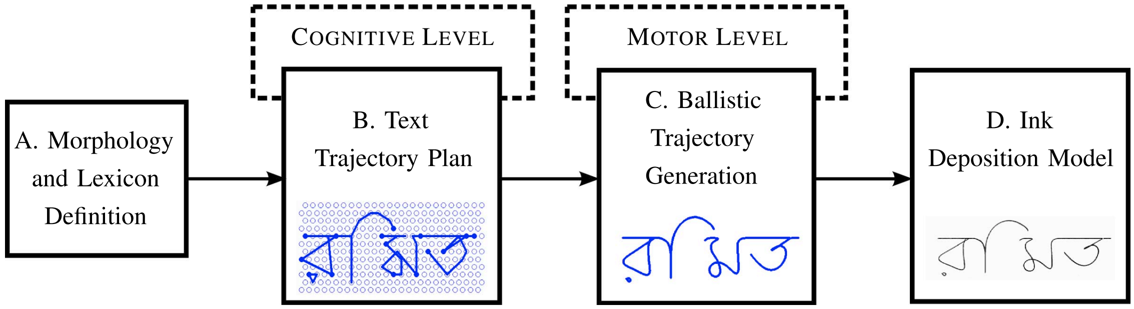

Fig. 2: Overview of the proposed system to generate a master signature

each script is an open issue nowadays.

Taking into account the mentioned lacks, the main contribution of this paper is a neuromotor-based model to generate static signatures in Bengali script. Specifically, we use a neuromotor inspired synthesizer [1] as the basis of the proposed Bengali static signature generator. In this contribution, we generate new identities and duplicates from synthetic specimens covering the intra and inter-personal variability, respectively. Using the only available static Bengali database [24], we will evaluate the closeness of our synthetic database and the real one through a performance analysis. An example of real and synthetic Bengali signature images is shown in Fig. 1.

The outline of the paper is as follows: Section II describes the neuromotor synthesizer to generate Bengali signature images. Section III is dedicated to the generation of a synthetic Bengali database. Experiments are discussed in Section IV and finally, the paper ends with some conclusions and future research ideas in Section V.

II. NEUROMOTOR APPROACH FOR BENGALI SIGNATURE GENERATION

As a follow-up work of [1], [2], in this work we have redesigned such previous signature synthesizer, developed under common concepts in neuroscience, to generate Bengali signatures automatically.

A handwritten signature is the final result of a complex system which involves cognitive and fine motor controls. To produce synthetic signatures, we have focused on the motor equivalence theory, which suggests that the brain stores in two levels the movements aimed at performing a single task like signing. The first level is irrespective of the muscles and stores in the brain the movement in an abstract form as spatial sequence of points which define the trajectory plan. The second level depends on the signer muscular skills as it consists of a sequence of motor commands to execute the final ballistic trajectory [25], [1], [2], [26]. This theory has mainly inspired the design of our off-lne handwritten Bengali signature synthesizer. This signature generator is built following the different steps shown in Fig. 2, which are summarized as: (A) The morphology and lexicon of Bengali handwritten signatures is firstly defined; (B) At the cognitive level, letters engrams as fundamental part of the trajectory plan are defined by hexagonal letter grids; (C) At motor level, the final ballistic trajectory is defined through several kinematic filters; and (D) A virtual ink deposition model is used to obtain realistic Bengali signature images.

A. Morphology and Lexicon Definition

To define a realistic synthetic Bengali signature images, its morphology and lexicon should be firstly modeled so as to generate human-like specimens. Apart from the script, one of the most different characteristic compared to Western signatures is that flourishes do not appear in Bengali signatures. They are mainly composed of two words which are related to the name and surname as it is shown in Fig. 1. Occasionally, a third word associated to the middle name could come out. By using the Bengali static signature dataset [24], we have calculated the distribution of the number of words per signature and letters per word as they are shown in Table I.

Similar to [27], we have also taken into account other characteristics which have been modeled through a Generalize Extreme Value (GEV) function. This function allows to model a natural phenomena with three parameters $\{\xi_i, \sigma_i, \mu_i\}$, namely location, scale and shape respectively. For this work we have modeled the number of letters, slant, skew, text width and text height. The parameters which define each GEV are shared in Table II. As the GEV distribution range is $(-\infty, +\infty)$, we have also determined the minimum and maximum realistic values of each distribution. It is worth pointing out that certain parameters have lower variability in Bengali script compared to Western one such as skew or slant. We refer interested reader to [27].

On the other hand, the signature generator is not loaded for real names owing to private reasons. Instead, we generate random names. Among all the Bengali characters, this script can be defined by 12 vowels and 40 consonants. In order to create realistic names, after defining the number of words and letters per word, we decide which letter should be included in the signature following the frequency in which each letter usually appears in Bengali handwritten. Moreover, this script does not have the concept of upper case or lower case letters, all letters have the same height, including the starting letter. Finally, the letters are usually connected at the head line region in a word. Instead, letters are generally connected in lower parts in Western style. To decide if a single letter is connected or not with the following one, we have used a simple random function.

TABLE I: Distribution of words and letters in the signature (%)

Word	Word per signature	Number of letter per word					
		1	2	3	4	5	6
1st	46.95	0.00	12.0	51.0	30.0	7.00	0.00
2nd	46.95	4.00	48.0	43.0	4.00	1.00	0.00
3rd	6.10	0.00	69.2	23.0	0.00	0.00	7.80

TABLE II: Parameters to model the Bengali signature morphology through GEV function $\{\xi_i, \sigma_i, \mu_i\}$

Parameter	ξ_i	σ_i	μ_i	min	max
Number of letters	-0.03	1.03	5.59	4.00	12.00
Slant (degrees)	-0.26	12.32	-4.75	-28.50	33.69
Skew (degrees)	-0.17	2.03	-0.94	-5.06	6.12
Text width (mm)	-0.12	30.54	148.9	98.82	251.8
Text height (mm)	-0.06	6.55	31.11	19.07	65.50

B. Text Trajectory Plan

To approach the cognitive level, our synthesizer takes into account the writing sequence of the text trajectory plan by the composition of each letter trajectory plan. It consists in two steps:

1) A hexagonal grid is initially defined. Its horizontal and vertical distances are defined as they are kept constant so as to design a specific writing style per signer [1], [2]. Since Bengali characters are more complex than Western ones, we had defined a denser grid in this work. Such denser grid is designed by aumenting its resolution.
2) Next, stroke limits are defined over the grid as well as the writing strokes order, which are kept constant per writer. To build the text trajectory plan, we connect directly each end and initial point of each consecutive letter. In Fig. 2 we could see the points to define the text trajectory plan of a word with the stroke limits highlighted on the grid.

Finally, to give more realism to Bengali synthetic signatures, the upperline of a word is kept constant in the grid, i.e., the upperline points' letters, which compose the trajectory plan, are located in the same row. It should be noted that the points defined in this section are not necessarily related to the so called target points in the cortex action plan. This part of the synthesizer is loosely based on the motor equivalence model theory but it does not pretend to model or simulate it.

C. Ballistic Trajectory Generation

To approach the motor level we have used the inverse model proposed for static Western signature generation [1], [2]. In Western signatures generation a multi-level motor scheme was used based on several kinematic filters to simulate the inertial action produced by three main parts: finger, forearm and wrist. Briefly, in Western signature generation, the finger was approached by an inertial filter applied to the whole engram related to the text trajectory plan; the forearm was simulated by a filter applied to the flourish engram; and the wrist by a filter applied to the whole signature because the wrist moves continuously when writing both the text and flourish. It was an approach inspired in the production of handwriting, but it does not necessarily mean that we model exactly the muscles action during the handwritten.

One of the main differences with respect to Western signature is that Bengali signatures do not include any flourish. This leads to reduce the number of inertial filters in this work as follows: i) The first filter is associated to the finger effect. So, we have programmed the filter in order to start and stop stroke by stroke. It corresponds to neuromuscular commands previously segmented in the text trajectory plan. This filter is most relevant to generate ballistic trajectories since Bengali script is composed of a lot of small strokes. ii) The second filter applied to the signature is the so called wrist inertial filter. Because the typology in Bengali signatures, this filter was reduced to the minimum. It heuristically imitates the wrist movement from left to write when they sign as therefore, it is applied to all the engram. Additionally, it has been noticed that certain strokes end in the middle of other strokes producing a contact point in the middle of them. To guarantee the continuity between these kind of strokes, according to this observation, the filtered trajectory is constrained to pass by these contact points.

To preserve the human-like appearance of the synthetic signature, several inertial filters could be used such as Bezier curves or Savitsky-Golay filter [22]. However, we found the use of Kaiser filters [1], [2] more flexible, whose finite impulse response $h^t[n]$ is defined as:

$$h^t[n] = \begin{cases} \frac{I_0\left(\pi\beta\sqrt{1-\left(\frac{2n}{N-1}-1\right)^2}\right)}{I_0(\pi\beta)} & 0 \leq n \leq N-1 \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

Where β is a shape factor fixed to 0.1 and N the filter length, which is related to the signing velocity. Being $N_f = L_f v^2$ for the finger inertial filter length and $N_w = L_w v^2$ for the wrist inertial filter. Both L_f and L_w represents inertial variables. Finally, v is associated to the signing velocity and it was modeled through a GEV function whose parameters are: $\{\xi_i, \sigma_i, \mu_i\} = \{-0.07, 0.65, 2.63\}$ in the range $(2.00, 5.00)$.

D. Ink Deposition Model

To obtain the off-line version of the signatures, we have 8-connected the signatures (i.e. the skeleton) with the Bresenham's lines algorithm and then we apply the virtual ink deposition model [22], [1], which use three kind of inks and different ballpoint pen sizes. Finally, signature image resolution is adjusted at 600 dpi.

III. BENGALI DATABASE GENERATION

In this section, we describe the procedure to adjust the proposed synthesizer in order to approach both the inter and intra-personal variability in Bengali signatures similar to each other [1], [2].

A. Generation of New Identities

The inter-personal variability is introduced at morphological, cognitive and motor levels in order to create master signatures. On the morphological level, we modify the signer full name according to the distributions given in Section II-A. On the cognitive level, the distance between rows and columns of the signer grid was set for each writer so as to design a text height and width letter style. On the motor level, the inertial variables (L_f, L_w) were randomly chosen from three to four times the distance between the grid nodes and kept constant for each writer.

Finally, because there are more stable signers than others, i.e. signers which repeat their own signatures with a high similarity among them, a stability parameter s is defined for each writer. A visual example of the capacity to generate several synthetic human-like signatures is shown in Fig. 3.

B. Generation of Duplicated Samples

Two handwritten specimens are never similar among other. Personal signatures executed by the same signer have particular modifications due to the pose, writing tool, emotional condition, etc. So, once the master signature is defined, the synthesizer generates new samples of the same master signature by some modifications.

On the morphological level, although the name is constant, parameters like skew, slant, average space between letters and words are slightly varied [27], [2]. Let p be the parameter value and mp be its range (the maximum value minus the minimum). Then, let s be the stability parameter, the value p is worked out for every generated sample as $p+u$, u being a random variable which follows an uniform distribution $\mathcal{U}(-mp/2, mp/2)$. If the modified value exceed the parameter range it is set up to the minimum or maximum value, accordingly.

On the cognitive level, the intra-personal variability is due to two parts: 1) We set up a circumference centered in each grid node, being its radius a source of variability per signer. In each signature repetition, the grid node is moved inside such circumference. 2) The signature engram nodes of each pen-down are horizontally and vertically displaced a distance randomly chosen between zero and half the grid distance between nodes. Such *engram nodes* refer to the limits of synthetic strokes. 3) Similarly to [19], [20], a sinusoidal transformation is applied to the engram nodes to simulate the synchronism variability in the muscles. Let's assume that (x_p, y_p) be the perceptual points coordinates; (L_x, L_y) be the signature width and height; (A_x, A_y) be the amplitude of sine and; (P_x, P_y) be the period, then this transformation is applied as follows:

$$\hat{x}_p = A_x \sin(2\pi P_x x_p / L_x) \quad \hat{y}_p = A_y \sin(2\pi P_y y_p / L_y) \quad (2)$$

where $(\hat{x}_p, \hat{y}_p)$ are the new perceptual point coordinates. The amplitudes are defined randomly between zero and twice the distance between grid points whereas the periods are random values in the range $\mathcal{U}(0, 2)$.

On the motor level, the parameters L_f and L_w are modified as the morphological ones. Visually, Fig. 4 shows artificial intra-personal variability achieved with this method compared to real signatures.

Finally, some of the parameters used in the Bengali signature generator are not strictly related to this script. For further details in these parameters, reader can refer to [1], [2].

IV. Experiments

The aim of the experiment is to evaluate the similarity between the synthetic and real signatures when they are examined from two completely different Automatic Signature Verifiers (ASVs). Thus, as real database we have used the Bengali-100 Static Signature DB [24], composed of 100 user and 24 repetition per individual (2400 signatures in total). As ASVs, we have used a geometric features followed by a HMM classifier [28] and a texture-based followed by an SVM classifier [29]. Both ASVs are based in completely different principles in order to obtain more generic conclusions.

Each ASV was trained by the following well-known procedure with T randomly selected signatures. Then, the remaining signatures are used for testing the False Rejection Rate (FRR). To calculate the False Acceptance Rate (FAR), we have used the genuine test samples from all the remaining users. All the experiments are repeated 10 times ($r = 10$). As such, the FRR is built with $(n_s - T) \times n_u \times r$ and the FAR by $(n_s - T) \times n_u \times (n_u - 1) \times r$. Where the number of signatures per user is $n_s = 24$ and 100 the number of total users n_u. So, in the case of $T = 5$, FRR is composed of $(24 - 5) \times 100 \times 10 = 19000$ scores and the FAR of $(24-5) \times 100 \times 99 \times 10 = 1881000$ scores. To imitate several realistic scenarios with few or many enrolled samples, T varies as: $(2, 3, 5, 8, 10)$. Finally, the results are given in terms of Equal Error Rate (EER) since this represents the operative points where FRR and FAR curves coincide.

Experimental results are shown in Fig. 5 through Detection Error Tradeoff (DET) curves, since they allow to analyze the behavior at several FAR and FRR points. We can qualitatively observe a tendency to achieve similar DET curves between the synthetic and the real Bengali database. Also, this phenomena is repeated in both systems (SVM and HMM) reinforcing the feasibility of the synthesizer to approach such behavior. Moreover, it is worth mentioning that excellent results are achieved when few signatures are used for training. As additional observation, it is noted that the DET curves are pretty similar in all operative points in the case of HMM, however higher similarity is seen in SVM for low values in the FAR curves. Regarding performance measures, we could compare the EER of real and synthetic signature in each case. Once again we could see that better similarities are achieved by HMM-based system, especially while dealing with reduced training sets. Nevertheless, promising results are also obtained with the SVM, which seems to be much sensitive to our synthesizer than HMM. Finally, the standard deviation is also given in the Fig. 5. It is calculated according to the 10 EER, obtained in each repetition of the experiment. A low value in all cases is being observed, which suggests the validity of the EER in all experiments.

V. Conclusion

This paper presents a novel solution to generate human-like synthetic static Bengali signatures. The signature synthesizer is

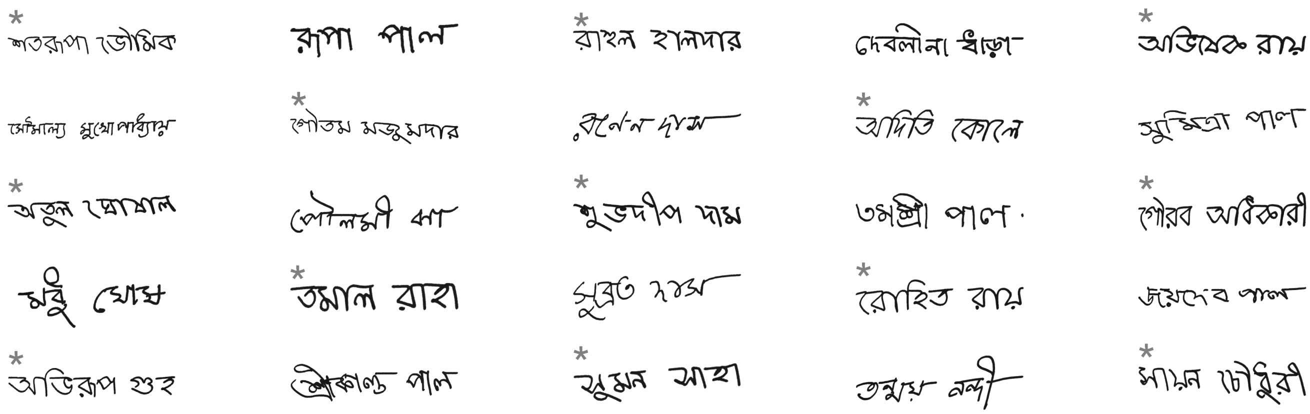

Fig. 3: Bengali examples of inter-personal variability. Synthetic signatures are market by an asterisk.

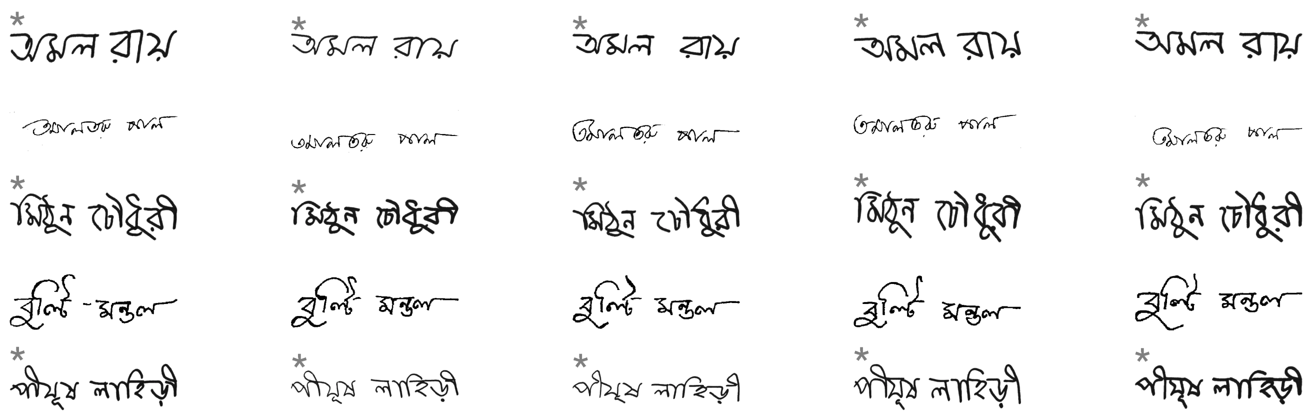

Fig. 4: Bengali examples of intra-personal variability. Synthetic signatures are market by an asterisk.

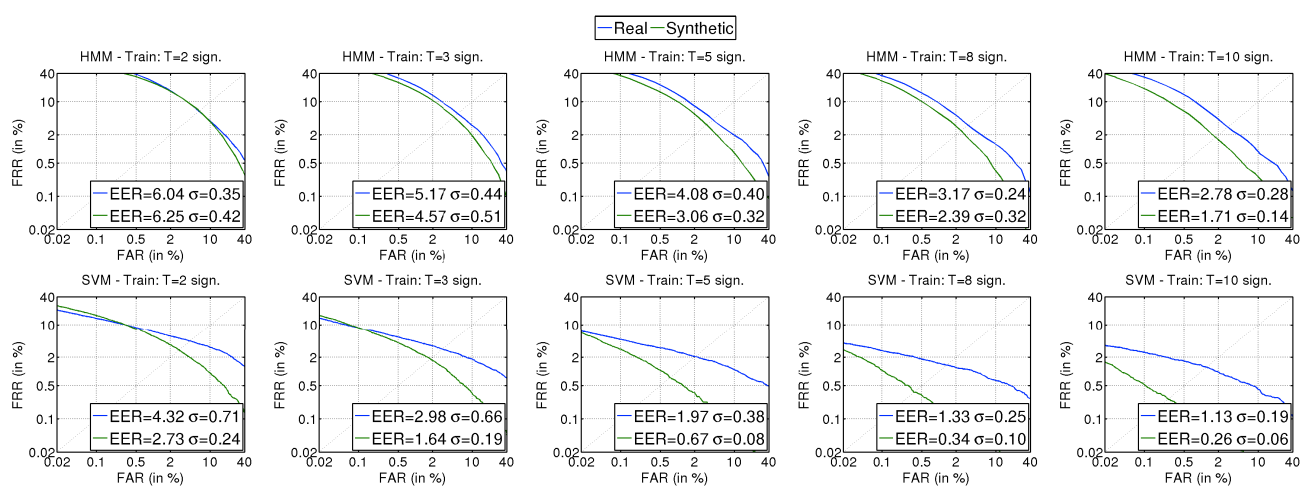

Fig. 5: DET curves to compare the closeness between a real and a synthetic Bengali database with two completely different ASVs: HMM and SVM.

inspired by motor equivalence theory which states that human action can be divided into a cognitive level and a motor level. Briefly, in this work we have redesigned a previous synthesizer [1], [2] which generates static Western signatures. This redesign implies major changes in the morphology definition of the language, the introduction of a letter engram and hexagonal grid to mimic the signature trajectory plan and the filters used to produce the ballistic trajectories.

To validate a proper signature generation, we took into account their realistic appearance as the comparison of the closeness performance regarding a real static Bengali database. Generating realistic signatures in appearance could be not mandatory for ASVs. However, keeping such realistic appareance in synthetic signatures leads to gain a better understanding of biological generation processes.

Due to the lack of research on Bengali script signatures, this static Bengali synthesizer emerges as an opportunity to create datasets to test systems, for security evaluations, scalability studies, etc. Our future work ideas rely on the multi-script generation by redesigning some stages in the synthesizer if it turns out necessary. Also additional experimental processes could be validated in future research such as visual Turing tests, the use of real signatures to train and synthetic to test and vice versa, and so on. Finally, research on dynamic signature generation is being also taking into account reporting promising results.

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