Event Based Offline Signature Modeling Using Grid Source Probabilistic Coding

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Abstract. A new offline handwritten signature modeling is introduced that confluences disciplines from grid feature extraction and information theory. The proposed scheme advances further a previously reported feature extraction technique which exploits pixel transitions along the signature trace over predetermined two pixel paths. In this new work the feature components, partitioned in groups, are considered as events of a grid based discrete space probabilistic source. Based on the 16-ary F_{CB2} feature, a set of 87 orthogonal event schemes, organized in tetrads, is identified. Next an entropy rule is drawn in order to declare the most appropriate tetrad scheme for representing a writer's signature. When skilled forgery is encountered verification results derived on both the GPDS300 dataset and a proprietary one, indicate enhanced EER rates compared to other approaches, including the previous reference of F_{CB2} as well.

Keywords: Signature Verification, Grid Features, Information Theory, Events.

1 Introduction

It is now entrenched throughout a vast collection of research papers and extensive surveys that the signature remains a popular way for humans to declare their identity in many application areas [1]. Automated Signature Verification Systems (ASVS) are broadly divided into two major categories depending on the method that the signature is acquired. Both online and offline ASVS must cope with the fact that the process of creating handwritten signatures, even when they originate from a well trained genuine writer, may carry natural variations, defined in the literature as inter-writer variability It is widely accepted that the online ASVS are generally more efficient when compared to offline ASVS. A commonly used figure of merit which many researchers employ in order to characterize the efficiency of their ASVS is the equal error rate (EER) which is calculated from the ROC or DET plots of both types of error rates.

Offline ASVS objective is to efficiently map an image into a mathematical space which will represent the image by means of its corresponding features and

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computational intelligence techniques [2]-[3]. Feature extraction is one of the most challenging tasks when ASVS are designed. There are many philosophies including global based methods which address the image as a whole and extract features from it [2], and local based methods which include geometrically and graph based approaches [4]-[5].

Another philosophy with potential increasing interest exploits the signature using a coarse or fine detail grid which is imposed upon the image. Then the features are calculated as a function of the granularity of the image grid. The reader may find relative references from the work of Baltzakis and Papamarkos [6], Vargas et al. [7], Kumar et al. [8], Impedovo et al. [9], Shekar and Bharathi [10], Swanepoel and Coetzer [11], Kalera et al. [12], Gilperez et al. [13], Parodi et al. [14] along with many others. In a recent work provided by Tselios et al. [15] a novel method was presented which models the signatures by considering the histogram of specific pixel transitions along predefined paths within pre-confined Chebyshev distances of two ($\mathrm{F_{CB2}}$ feature). The feature extraction ideas have been evolved by modeling the feature components in a probabilistic context which allows us to represent the feature generation procedure as a discrete space random source. The $\mathrm{F_{CB2}}$ symbols (messages) that the random source outputs when a signature pixel is accounted are considered to be members of a predetermined alphabet. They are handled according to the description of the event concept and they are complemented along with their corresponding probabilistic moments. Thus, the 16 possible combinations of $\mathrm{F_{CB2}}$ transition paths are organized in groups with the use of an F_T-event collection where subscript T denotes the size of each feature group [16]. The result is an evolved feature description which is expected to enhance the representation of handwriting. An example is provided by selecting the 87 orthogonal permissible groups of four F_4 collection tetrads, hereafter called ‘schemes’, where in group formation orthogonality and non-redundancy constraints are taken into account. During the training phase the most appropriate event scheme is selected in order to represent each genuine writer by an ad-hoc minimum entropy selection algorithm. Verification results have been drawn with the use of two databases, the GPDS300 and a proprietary one by means of the EER figure of merit.

The remaining of the work is divided as follows: Section 2 provide the preprocessing stage and the feature extraction method. Section 3 describes the verification protocol and section 4 provides the preliminary results along with the conclusions.

2 Feature Extraction Method

2.1 Preprocessing Steps

The preprocessing of scanned signature images consists of signature black and white conversion, skeletonization, cropping and segmentation. Initially, greyscale images are converted to black and white using Otsu’s thresholding method [17]. Then, the morphological operation of signature’s skeleton extraction is applied on the black and white signature image to eliminate the effects of the pens’ ink variety, while preserving strokes' connectivity [2]. The most informative window (MIW) of the bounding rectangle is found in a similar way as in [15] and the part of signature's image outside this rectangle is cropped out. The outcome of the preprocessing steps outcome is depicted in Fig. 1.

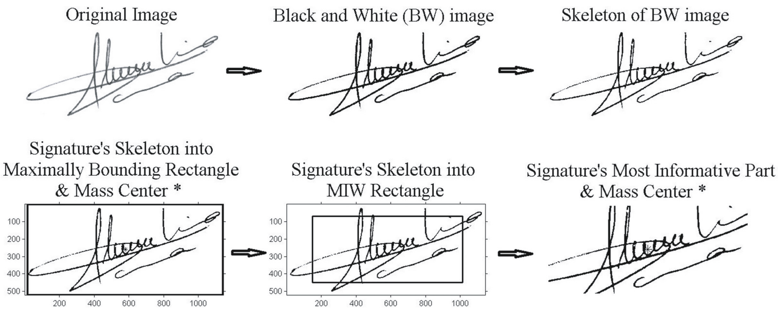

Fig. 1. Signature's Scanned Image Preprocessing Steps

Feature vectors can be extracted from the whole MIW of the signature, from segments of signature's MIW or from their combinations. Signature's MIW segmentation is an extension of the idea of equimass sampling grids [18]-[19]. The equimass sampling grids approach divides the number of black pixels of an image, denoted as mass, by the number of grid divisions in $x-$ or $y-$ direction. Then grid lines are placed in each direction such that each grid strip approximately contains an equal amount of black pixels. Equimass sampling grid segmentation provides strips of the signature with uniform size of signature pixels instead of the trivial distance grid segmentation which provides segments of equal area. The segmentation technique is further enhanced by relaxing the 'grid'-constraint of signature's MIW. This is achieved by keeping the approximately equal mass per segment constraint. Therefore, grid lines are placed in either $x-$ or $y-$ direction such that each grid strip contains the same number of black pixels, equal to mass divided by the number of strips. Each strip is segmented independently of each other, such that (approximately) equimass criterion holds among each segment of the strip. In this way, the resulting segmentation is not a grid segmentation, but an almost equimass rectangular image segmentation. The result is depicted in Fig. 2.

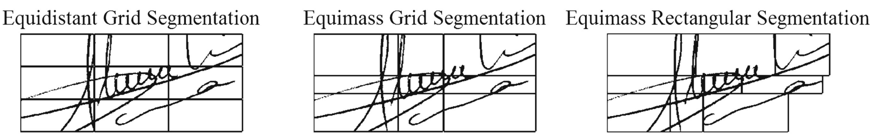

Fig. 2. MIW Signature Segmentation Techniques

2.2 Grid Based Feature Extraction

The proposed representation of the MIW of an offline signature in the feature space pursues modeling the distribution of the co-occurrences of black pixel transition paths of the signature strokes. The set of black pixel transition paths that are used as a basis for signature strokes modeling is the set of F_{CB2} pixel transition paths, in a slightly relaxed sense to the definition provided in [15]. To be specific, F_{CB2} transition paths comprise of three consecutive pixels while maintaining the constraint of having the first and third pixels restrained to a Chebyshev distance equal to two. Since, in offline signatures, signature-pixel ordering is unknown, the ordered sequence of the pixels cannot be estimated. This reduces the number of queried F_{CB2} transition paths, in a 5×5 pixel grid window, with center pixel each black pixel of signature's image, to the 16 independent transition paths presented in Fig. 3. The relaxation introduced now, compared to the definition of [15], is on the constraint of the three consecutive pixels being part of one-pixel wide signature trace. Through experimentation it was concluded that forcing the signature trace to be one-pixel wide, reduces the ability of F_{CB2} co-occurrence modeling. Thus, one-pixel wide constraints have been eliminated. This relaxation has no impact on the 16 basic F_{CB2} elements of the basis used for signature modeling.

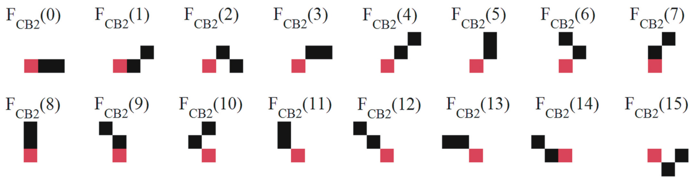

Fig. 3. The basis of the 16 F_{CB2} transition paths (center pixel of the 5×5 grid in red)

2.3 Event Based Modeling

Let (Ω, B, P) denote the probability space on which all our possible outcomes are defined. By definition, Ω is the sample space which consists of all 16 F_{CB2} components (symbols) produced by a discrete memory-less source whereas B is a sigma field (the event space) that contains all possible occurrences of symbols' combinations from the F_{CB2} alphabet. That is, B is the largest possible σ-field [20] which is the collection of all subsets of Ω and is called the power set. Discrete symbols of the sequence are produced at the center pixel of the 5×5 moving grid as it slides over the signature trajectory. In addition, the usual independent variable of time that normally applies a specific ordering to the data is not existent here, as it is of interest only the occurrence of symbols and not their ordered sequence. It is advantageous in our case to explicitly treat the notion of the signature pixels indexes (i, j) as a transformation of sequences produced by the source. As a consequence, the feature extraction grid can be identified as a discrete space - discrete alphabet source.

To overcome the problem of 2^{16} space management we group Ω into T subsets and we define the sub-s-fields B_t as the power sets for each Ω. In this work we choose to group the 16-$\mathrm{F}_{\mathrm{CB2}}(i)$ components into ensembles of four tetrads (call it hereafter F_4-collection) thus resulting to $4 \times 2^4 = 64$ possible event combinations. According to the exposed material, a discrete source, designated as S_n, can be defined by its emitted symbols and consequent events which are now members of one F_4 collection. The entropy of source S_n is defined as in [1], where $p_{S_n}(\alpha)$ is the distribution of the source events α. This novel modeling of the feature generation process is an evolution of the previous method as it was described in [15]. It attempts to model the distribution of the signature pixel transitions as an information source, while the F_4 collection has been utilized in order to extract events of features along with their corresponding probabilities.

$$H_{F_T} = H(S_n) = -\sum_{\alpha \in S_n} p_{S_n}(\alpha) \ln(p_{S_n}(\alpha)) \tag{1}$$

From the complete set of all the possible ensembles of the F_4 collection only 87 orthogonal cases (hereafter denoted as schemes) shall be enabled along with their corresponding probabilities. The term orthogonal denotes that each component in a subspace of a F_4 tetrad event set cannot be derived as a union of the same subspace F_4 event combination. This constraint provides each signature with 87 different F_4 orthogonal tetrads event sets, found through exhaustive search. In the verification stage that follows, a selection algorithm must be applied in order to choose the most appropriate scheme for each writer. The set Ω, along with one of the feasible orthogonal F_4 partitions ($T = 4$) and its accompanied power set is depicted in Fig. 4.

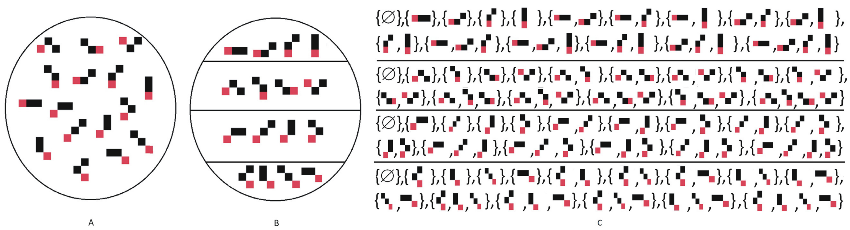

Fig. 4. (A) Sample space, (B) One orthogonal F_4 collection (c) Power set for each tetrad

3 Verification Procedure

3.1 Verification Protocol

During the training phase for each writer and all of his signatures samples and segments an appropriate common scheme should be selected. We call hereafter the set of the appropriate schemes per segment for feature extraction as the representative schemes set (RSS). The selection of the RSS of an orthogonal F_4 collection of $\mathrm{F}_{\mathrm{CB2}}$ for signature modeling in the current approach is based on the criterion of the most uniform event distribution. The intuition behind this criterion is that the more uniformly the $\mathrm{F}_{\mathrm{CB2}}$ components along with their set of events are met, the more relevant is the selected scheme to the signature's trace underlying mapping of motor movement. The uniformity of the distribution of symbols within a group g of $\mathrm{F}_{\mathrm{CB2}}$ components is evaluated using the entropy of the probability mass function P of the sixteen possible combinations of each F_4 collection within each g group. For each one of the four power sets of a F_4 collection an entropy value is calculated namely $H_{41},, H_{42}, H_{43}$ and H_{44}. The sum of them identifies the representative entropy for the scheme applied on the examined signature trace. The RSS is determined from the reference set as defined in section 2.3. For a segment the RSS is the one that provides the minimum sum of entropies along the relevant segment of nref number the signatures of the reference set:

$$H_{F_4} = \sum_{g=1}^{4} H_{4g}, \quad H_S = \sum_{\mathrm{nref}} H_{F_4}, \qquad \mathrm{RSS} = \mathrm{argmin}\{H_S\}, s = 1:87 \tag{2}$$

For each signer, nref number of genuine and an equal number of simulated-forgery signature samples are randomly chosen for training the classifier. The genuine samples are used initially to determine the RSS. Then, the feature vectors of all signatures of the reference set are extracted using the RSS and feed a hard-margin SVM classifier using radial basis kernel. The remaining genuine and simulated forgery signatures' feature vectors using the determined RSS feed the SVM classifier directly for testing, similar to SVM FLV scheme used in [15]. In our implementation, the SVM classifier apart from the class decision, calculates a score equal to the distance of the sample under test from the SVM separating hyperplane. This score for all tested signatures and for all writers is then used for the calculation of the Equal Error Rate (EER) of the proposed system using a global threshold. The experiments are repeated 20 times and the reported results are the mean values of experiment's repetitions, so that results have greater statistical significance.

3.2 Databases

The efficiency of the proposed method has been investigated with two databases of 8-bit grey scale signatures: a Greek signers' (CORPUS1) [15] and GPDS-300 (CORPUS2) [7]. CORPUS1 is comprised from 105 genuine and 21 simulated forgery signature samples for each of the 69 signers of the database. CORPUS2 has 24 genuine signatures and 30 simulated forgeries for each of the 300 signers of the database and is publicly available. During the experiments two schemes of randomly selected training and testing samples were used for comparison with the outcomes of contemporary research in the field. In the first scheme, 12 genuine and 12 simulated-forgery reference samples per writer are used, while in the second scheme 5 genuine and 5 simulated forgery reference samples are used.

The remaining samples are used for testing. The feature vector is a combination of feature extraction from the whole signature's MIW and from the four segments of the 2×2 equimass rectangular segmentation of the MIW relevant to 'S2' scheme used in [15] for comparison.

4 Verification Results and Comparisons

According to the discussion presented above, FAR, FRR and the relevant EER rates, are evaluated for (a) CORPUS 1 withnref = 5 and nref = 12 and (b) CORPUS 2 with nref = 5 and nref = 12. The corresponding results are presented in Table 1 by means of the minimum mean FAR, FRR and EER values for the repetitions of the experimental sets of the current work. The results are promising compared to recently reported ones. In the case of CORPUS 1 the derived results are compared with the results relevant to those reported in [15] for feature level simulated forgery verification tests using 'S2' scheme using (a) nref = 5 and (b) the mean value of nref = 10 and nref = 15 tests for comparison with our test using nref = 12 and presented in Table 2. Concerning CORPUS 2, the results of recently reported research work using nref = 5 and nref = 12, along with the results of the current approach are presented in Table 3.

Table 1. Experimental Results: Mean FAR, FRR and EER values for the defined experimental sets for minimum observed EER values

Experimental Set	**FAR (%)**	**FRR (%)**	**EER (%)**
Corpus 1, nref = 5	2.59	4.23	3.42
Corpus 2, nref = 5	11.29	5.48	8.37
Corpus 1, nref = 12	1.77	2.01	1.83
Corpus 2, nref = 12	6.52	3.23	4.88

Table 2. CORPUS 1: Comparison results of EER (%) values with relevant framework in [15]

[15] for nref = 5	9.16	Current work for nref = 5	3.42
[15] mean EER for nref = 10 and nref = 15	4.65	Current work for nref = 12	1.83

Table 3. CORPUS 2: Comparison results of EER (%) values with recent research approaches

[15] for nref = 5	12.32	Current work for nref = 5	8.37
[7] GPDS-100 for nref = 5	12.02		
[14] nref = 13 (only genuine train samples)	4.21	Current work for nref = 12	4.88
[7] for nref = 12	6.2		
[15] mean EER (nref = 10) & (nref = 15)	8.26		
[8] for nref = 12	13.76		
[21] for nref = 12	15.11		
[22] nref = 12 (only genuine train samples)	15.4		

5 Conclusions

In this work a handwritten signature model based on the powerset of an event topology is evaluated for offline signature verification. Early results on two signature databases suggest that the proposed feature extraction method is promising; It is the authors intention to follow the dissimilarity framework in order to verify the effectiveness of the proposed approach.

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