An Extended-Shadow-Code Based Approach for Off-Line Signature Verification: Part -I- Evaluation of the Bar Mask Definition

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Abstract

In this paper, the authors present an evaluation of the extended shadow code (ESC) used as a global feature vector for the signature verification problem. The proposed class of shape factors seems to be a good compromise between global features related to the general aspect of the signature, and local features related to measurements taken on specific parts of the signature. This is achieved by the bar mask definition, where at low resolution the ESC is related to the overall proportions of the signature. At high resolution, values of the horizontal, vertical and diagonal bars could be related to local measurements taken on specific parts of the signature without requiring low-level handwriting segmentation which is a very difficult task.

1: Introduction

As reported by Sabourin *et al.* in a recent survey of the literature [1], two approaches have been adopted by various researchers in the field of off-line signature verification for the definition of shape factors tailor-made for the elimination of random forgeries.

A classical approach consists in taking local measurements on specific parts of the signature. This class of method is said to be *text-sensitive* because it necessitates the segmentation of specific letters (a very difficult task in practice which has not been yet solved) or the segmentation of specific primitives. Moreover, this is not a general scheme to follow, especially if the signatures are highly personalized, like European signatures.

A second approach consists in using global measurements taken on the silhouette of the signature considered as a whole. As examples, the coefficients of the Hadamard or the Fourier transforms, curvature or directional histograms, etc. could be related to the class of global shape factors. This class of method is said to be *text-insensitive*: more general than the former approach, but less powerful.

Consequently, we propose in this paper a way to go about finding a solution to the complex task of shape factor definition tailor-made for the off-line signature verification problem in the context of random forgeries. A first evaluation of the *extended shadow code* used as a shape factor for signature verification has been presented in [2]. The purpose of this paper is to evaluate the effect of the resolution of the bar mask array on verification performance.

2: The *extended shadow code* (*ESC*)

2.1: Shape factor definition

Burr has proposed the *shadow code* as a global shape factor tailor-made for handwritten character recognition [3,4]. This shape factor consists in the superposition of a bar mask array over the binary image of a handwritten character (see [2] for examples). Each bar is assumed to be a light detector related to a spatially constrained area of the 2D signal. A shadow projection operation is defined as the simultaneous projection of each black pixel into its closest horizontal, vertical, and diagonal (*HVD*) bars. A projected shadow turns on a set of bits distributed uniformly along the bar. After all the pixels on a thresholded piece of handwriting are projected, the number of on-bits in each bar is counted. The representation $R(\gamma)$ of the signature in feature space $\mathfrak{R}^n$ is therefore represented by a feature vector with cardinality n equal to the number of bars, with the numerical values normalized to the range [0, 1].

2.2: Definition of bar mask representations R(γ)

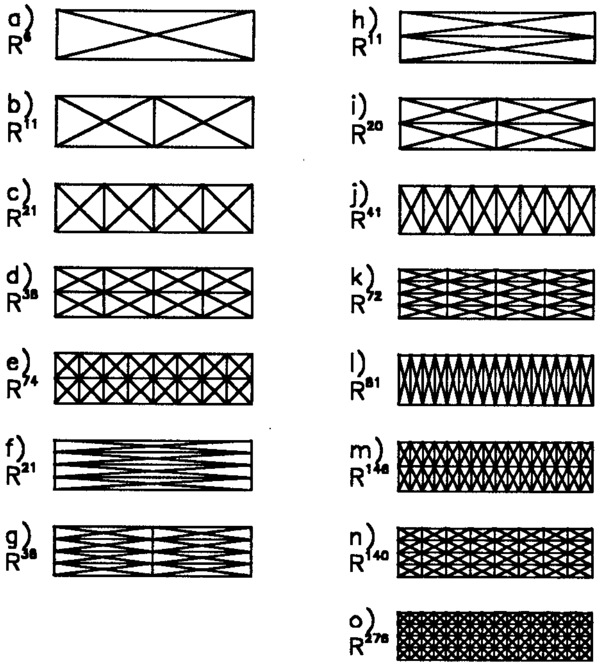

Figure 1

Fifteen bar mask representations R(a) to R(o) related to the *extended shadow code* evaluated in the context of signature verification are depicted in Figure 1. All signature images were digitized with a vidicon camera and a standard frame-grabber. The spatial sampling produces an image format of 128*x*512 pixels. Consequently, all representations R(γ) are derived from representation R(a) with code values ranging from 0 to 512 and from 0 to 128 for the horizontal and vertical bars respectively. The lengths of the horizontal (*H*) and vertical (*V*) bars of a representation R(γ) correspond to:

$$length(H) = \frac{512}{h},$$

$$length(V) = \frac{128}{v}, \quad with$$

$$h = \{1,2,4,8,16\} \quad and \quad v = \{1,2,4\}.$$

Finally, the length of diagonal bars (*D*) is defined as

$$length(D) = INT(\sqrt{length(H)^2 + length(V)^2}).$$

The highest resolution is achieved with representation R(o), where the length of the horizontal and vertical bars is 32, and that of the diagonal bars is $32\sqrt{2}$ [2].

2.3: Justification

One important characteristic that a shape factor related to the handwritten signature verification problem should have is the ability to be text-insensitive. This means that measurements taken on the signature shape do not relate to specific letters. This is especially important in the case of handwritten signatures characterized by well-written to highly personalized signatures. The main problem with global features is a lack of knowledge about the location of local measurements taken on the signature considered as a pattern when they are combined together for the definition of the feature vector.

Intrinsically, the *extended shadow code* is a global shape factor. The rationale behind the use of the *ESC* as a shape factor tailor-made for the signature verification problem is that it permits the local projection of the handwriting without losing the knowledge of the location of measurements in the 2D space. Thus, this shape factor seems to be a good compromise between global features related to the general aspect of the signature, and local features related to measurements taken on specific parts of the signature without requiring the low-level segmentation of the handwriting into primitives, which is a very difficult task. This is achieved by the bar mask definition, where at low resolution representation R(a) for example, the *ESC* is related to the overall proportions of the signature. In the opposite case, the values of the HVD bars of representation R(o) could be related to local measurements taken on specific parts of the signature without the segmentation of specific letters or specific primitives. In this way, varying the resolution of the bar mask permits the definition of shape factors ranging from purely global to almost local.

The last point that should be taken into account is that *ESC* as shape factor is not invariant in scale, translation and rotation. Consequently it is necessary to normalize the signature image before projecting the pixels (located on the signature line) on the bar mask array. Following the hypothesis that handwritten signatures are the result of a rapid movement, we have supposed that:

- the local variability of handwriting could be relatively consistent, and
- the overall orientation of signatures written in a 2D constrained area could be relatively stable as well.

This proposition is supported by experts in the field of forensic science. Following Harrison [7], the proportions of handwritten signatures and the general orientation of the signature on any form are assumed to be related to the intrinsic characteristics of the writer's identity when the writing process is guided by the box or the area on the form. Consequently, the only transformation made on the silhouette of the signature is a correction in translation.

3: Signature database description

The proposed signature verification system has been tested using a standard signature database of 800 images (40 signatures written by 20 individuals) [2,5,6]. Signatures were written by hand in a 3x12 cm rectangle, using the same type of writing tool (a Pilot Fineliner with a flexible felt tip and black ink) and white sheets of paper. Let $\boldsymbol{R}$ be the reference database related to the first 20 signatures written by each writer ($|\boldsymbol{R}|$ =400), and $\boldsymbol{T}$ be the test database which is related to the last 20 signatures of each writer, with $|\boldsymbol{T}|$ =400.

Let χ be the set of all feature vectors related to a bar mask representation R(γ), with $|\chi|$=800. $X_i = \{x_{i1}, x_{i2}, \ldots, x_{im}, \ldots, x_{iN}\}$ represents a feature vector from the test set $\boldsymbol{T}$, with $X_i \in \boldsymbol{T} \subset \chi$; and $Y_j = \{y_{j1}, y_{j2}, \ldots, y_{jm}, \ldots, y_{jN}\}$ a feature vector from the reference set $\boldsymbol{R}$, with $Y_j \in \boldsymbol{R} \subset \chi$. As we mentioned earlier, the size of each feature vector $\chi_i \in \chi$ varies from N=6 with representation R(a) to N=276 with representation R(o) depending on the experiment [Figure 1].

Let us define the sets required for the performance evaluation of the classifiers assigned to each writer *(i)* enrolled in the verification system. Let the set of genuine signatures $S^{(i)}_{ref} \subset \boldsymbol{R}^{(i)}$ required as reference signatures be retained for the minimum distance classifier with threshold $\tau^{(i)}$. The cardinality of this comparison set will be $|S^{(i)}_{ref}| = N_{ref}$. The comparison signatures are chosen randomly in the reference set $\boldsymbol{R}^{(i)}$, with $|\boldsymbol{R}^{(i)}|$ =20.

Let the learning set $S^{(i)}_{learn} \subset \boldsymbol{R}$ of cardinality $|S^{(i)}_{learn}| = N_{learn}$ be used for the evaluation of threshold $\tau^{(i)}$ for writer *(i)*. Learning set $S^{(i)}_{learn}$ is defined by the genuine signatures of writer *(i)* which were not chosen for $S^{(i)}_{ref}$ (class ω_1), and by 5 signatures chosen randomly from all sets $\boldsymbol{R}^{(i)}$ of the other writers, that is, 5x19 random forgeries related to class ω_2.

Set $S^{(i)}_{gen} \subset \boldsymbol{T}$ of writer *(i)* is used for the evaluation of the performance in generalization of each classifier, with $|S^{(i)}_{gen}| = N_{gen}$. Set $S^{(i)}_{gen}$ is made up of 20 genuine signatures from test set $\boldsymbol{T}^{(i)}$ of writer *(i)* (class ω_1), and by 5 signatures chosen randomly from all sets $\boldsymbol{T}^{(i)}$ of the other writers, that is, 5x19 random forgeries related to class ω_2; consequently, the cardinality of all sets $S^{(i)}_{gen}$ is $|S^{(i)}_{gen}| = N_{gen}$=115. Thus, a statistical independence of sets $S^{(i)}_{gen}$, $S^{(i)}_{ref}$ *and* $S^{(i)}_{learn}$ is observed because initial sets $\boldsymbol{R}$ and $\boldsymbol{T}$ have this property.

4: Numerical experiments

4.1: Experiment I

A *kNN classifier with a vote* allows evaluation of the discriminant power of the proposed shape factor in the context of the signature database under consideration. This can be related to a lower limit of the total error rate when the maximum available information is kept in memory. The euclidian distance $d(X_i,Y_j)$ used for the search of the k *N*earest *N*eighbors (*kNN*) $Y_j \in S^{(i)}_{learn}$ of feature vector $X_i \in S^{(i)}_{gen}$ under evaluation is defined as

$$d(X_i,Y_j) = \|X_i - Y_j\| = \left\{ \sum_{m=1}^{N} (x_{i,m} - y_{j,m})^2 \right\}^{\frac{1}{2}}$$

The classification of a feature vector $X_i \in S^{(i)}_{gen}$ results from the comparison of the corresponding class label (ω_1 *or* ω_2) with the class labels associated with its k *N*earest *N*eighbors $Y_i \in S^{(i)}_{learn}$.

This procedure is used for all observations $X_i \in S^{(i)}_{gen}$ of writer *(i)*, and is repeated for the 20 writers enrolled in the signature database. Let us recall that $|S^{(i)}_{learn}| = |S^{(i)}_{gen}| = 115$, with subsets related to class ω_1 of cardinality 20 and subsets ω_2 of cardinality 95. An experiment was conducted to evaluate the effect of the definition of datasets related to class ω_2. Thus, the previous experiment was repeated 25 times and the observations of class ω_2, that is, the subsets of $S^{(i)}_{learn}$ and $S^{(i)}_{gen}$, were redefined randomly following the protocol presented in section 3.1. At the end of the evaluation process, the mean performance $\bar{\epsilon}_t$ of the verification system was evaluated, with k={1,3,5,7,9}.

The best results were achieved with the *1NN* classifier (k=1) for all representations R(γ) [Figure 2]. The mean total error rate $\bar{\epsilon}_t$ of the verification system using representation R(a) is 2.156% (0.330). It is very difficult to compare these experimental results with others published in the literature because the signature databases and experimental protocols used for the performance evaluations are always different. But the experimental results presented here compare favorably with those we obtained using the same experimental protocol and signature database. As an example, the performance of the directional PDF proposed as a global shape factor [5,6] is clearly of less interest than the performance obtained using the *extended shadow code*. In fact, the mean total error rate $\bar{\epsilon}_t$ is around 2.69% (0.20) with a dimensionality of the feature vector of $\Re^{18}$.

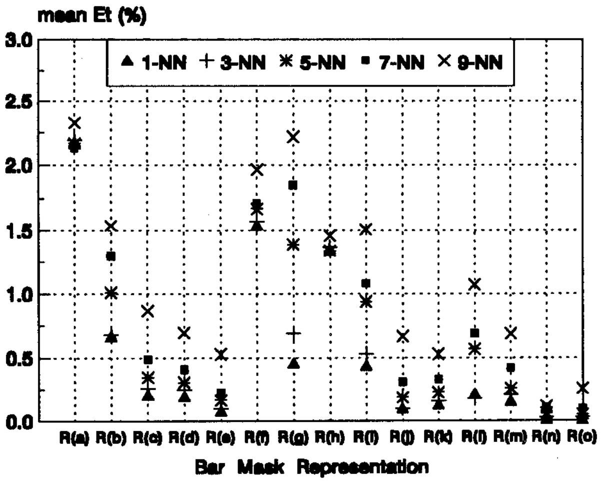

Figure 2

Following the analysis of the numerical results depicted in Figure 2 (for the 1NN classifier), shape factors R(e), R(j), R(n) and R(o) show a mean total error rate $\bar{\epsilon}_t$ below 0.1% with a dimensionality of 74, 41, 140 and 276 respectively. On the other hand, only 4 shape factors show a mean total error rate $\bar{\epsilon}_t$ in the [0.500% - 2.156%] range; that is, R(a), R(b), R(f) and R(h) with a dimensionality in the feature space of 6, 11, 21 and 11 respectively.

4.2 Experiment II

A *minimum distance classifier* that is more realistic for this kind of application has been used. An experiment was designed to evaluate the effect of the choice and the number of reference signatures [section 3.1], that is, the definition of set $S^{(i)}_{ref}$ for the global performance of the verification system [Figure 3]. It is interesting to note that all the experimental results show a mean total error rate $\bar{\epsilon}_t$ below 1.00% for $N_{ref} \geq 4$ genuine signatures using representations R(n) and R(o). These results show experimentally that representation R(n) could be considered as the upper limit in terms of bar mask resolution for this signature database. The reduction in dimensionality of the feature vector is appreciable, with $\Re^{140}$ for representation R(n) compared with $\Re^{276}$ for representation R(o).

Moreover, the performance of all signature verification systems seems stabilized at around $N_{ref} = 6$ genuine signatures. The worst cases were achieved with representations R(f), R(a), R(g) and R(h), showing a mean total error rate $\bar{\epsilon}_t$ between 4.524% (0.534) and 3.565% (0.716). It is very interesting to note the performance obtained with representation R(a), which is considered as a global shape factor. Compared with the directional PDF [5,6], using the same protocol with $N_{ref} = 6$ and the same signature database, the mean total error rate $\bar{\epsilon}_t$ was 6.46% (0.60). This confirms the high discriminant power of the *ESC* used as a shape factor tailor-made for the signature verification problem in the context of random forgeries.

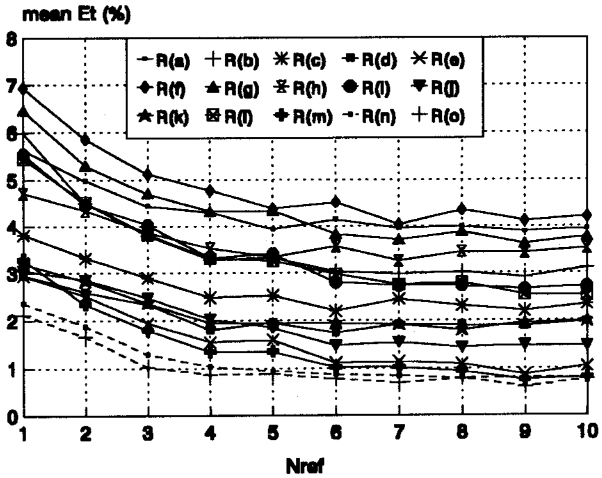

Figure 3

5: Conclusions

Taking into account the spatial location of local measurements seems to be helpful in the definition of shape factors in the context of signature verification. The experimental results presented here, however, compared favorably with those we obtained using the same experimental protocol and signature database.

6: References

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