Shape Matrices as a Mixed Shape Factor for Off-line Signature Verification

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Abstract

Shape matrices have been used as a representation of planar shapes like industrial parts or printed characters. In this paper, we investigate the use of shape matrices as a mixed shape factor for off-line signature verification. By mixed shape factor we mean any global shape factor where the position of local measurements are take into account in the definition of a similarity measure between two representations. It was demonstrated that using a good similarity measure between two shape matrices, this shape factor is relatively well suited for the global interpretation of signature images.

1. Introduction

A lot of works have been done in the field of automatic signature verification since the last twenty years. The first goal for sure lies in the elimination of random forgeries defined as genuine signatures of other writers enrolled or not in the signature verification system. This class of forgeries should be eliminated in practice for real applications like bank cheques authentication [1].

In fact, the elimination of random forgeries is a trivial task for human beings in general but it still an open problem for the computer. All approaches proposed in the field of automatic signature verification are based on a local or on a global analysis of the signature. This means the utilization of local or global shape factors (see [2] for a recent survey). In brief, local approaches necessitate the identification and the matching of local features (linear or curvilinear strokes, end points, junctions, etc.) located on the signature line. On the opposite, global approaches (ex: invariant moments, 2D transforms or histograms of directional data) make use of the whole signature in their analysis. In this way, the problem related to the segmentation of the signature image in primitives is overcome.

1.1 Motivation of the work

A short analysis of the methodology used by human beings when they are in a situation of comparing two shapes, reveals that a global analysis of the scene is adopted when the task evolved is trivial; for example a car can be discriminate from a tree very quickly. But a local analysis is selected dynamically when the task is more difficult to solve. For example discriminating between two cats with approximately the same color (texture) and size necessitates a deeper analysis of the scene. In the case of the signature verification task, a global shape factor seems a natural choice for the elimination of random forgeries because the general aspect of the signature is sufficient for human beings in general to discriminate very quickly between genuine signatures and random forgeries. But global approaches never have a great success because the high intra-class variability of genuine signatures.

Several preprocessing algorithms used for emphasize some local characteristics (*perceptual features*) of the signatures are discussed in section 2. The shape matrices are defined in the next section 3. Experimental results are shown in section 4 and this is followed by a short discussion on related topics.

2. Preprocessing

All gray level images were binarized with the use of the classical Otsu's method. This algorithm seems sufficient for this signature database. After thresholding, a noise removal procedure is applied systematically on binary images in attempt to clean some spatial noise characterized by very small blobs (1 to 5 pixels). A simple morphological filter has been chosen for this preprocessing step.

2.1 Loop filling

The goal of this preprocessing step is to focus attention to loops in term of the presence/absence, and in term of their relative size and position. Since the class of images under study is closely related to handwriting, it is usual to deal with open loops too. For example, specimen a) depicted in Figure 1 is characterized by the presence of a big loop at the beginning of the signature; this loop is not always closed from one specimen to the other. From a perceptual point of view, those loops should be considered in the same way than closed loops. For these reasons, the

loop filling algorithm proposed in [3] has been implemented as a solution for this problem. In brief, this preprocessing algorithm put some emphasis on loops (perceptual primitives) without affecting the cursive aspect of the signatures [Figure 2].

2.2 Smearing

The smearing is a very simple mechanism consisting in the horizontal tracing between two sets of pixels (strokes). This is valid if the horizontal distance between two black pixels transition is below or equal to a threshold value fixed to 30 pixels in this experiment. As it can be seen in Figure 3, this preprocessing scheme eliminates in some way the cursive aspect of the signature including the lost of fine details. In other words, this process reinforce the body of the signature specially if the signature look like cursive script (see b) and d)). Smearing with a fixed threshold put emphasize on the presence of narrow loops (ex. c)) and relax at the same time the presence of big loops as in a); when loops vary in size, local variations are enhanced by the smearing mechanism. Inter-word spacing can produces also some ligatures as in d); in this case all fine details have been wiped out.

2.3 Smearing and loop filling

Applying the last two preprocessing algorithms in turn result in the extraction of the silhouette of the signature where the peculiarities of the handwriting are preserved [Figure 4]. The global analysis of the scene will not concentrate specifically on loops or on the body of the signature but on the global envelope of the shape. In this way, fine details are through away and the general aspect of the silhouette of the signature will serve as a visual cue for the global analysis of the scene. Specimens characterized by the presence of big loops will dominate the 2D space.

2.4 Pseudo-convex hull by morphological closing and loop filling

Finally, more fine details are preserved if the silhouette of the signature is the result of the application of the classical morphological closing procedure using a disk of diameter of 10 pixels and followed by the loop filling algorithm [Figure 5]. The cursive aspect of legible handwritten signature is more visible using this approach [see Figure 5d].

3. Shape factor definition

Shape Matrices (SM) have been proposed initially for the recognition of planar shapes [4,5]. More recently, it was shown that SMs can be use also for the interpretation of line images [6]. Let us recall briefly the definition and properties of the SM.

3.1 Polar sampling

The first step consists in the *polar sampling* of the silhouette of the pattern under study. Let

SM = a Shape Matrix of dimension *NS*x*NR* elements,
O = the center of gravity of the pattern to be encoded,
OA = the maximum radius of the pattern of length *L*,
MS = the maximum number of sample points on maximum radius (in pixels), $MS = INT(L) + 1$,
NS = the total number of sample points on maximum radius (in pixels), with $NS \leq MS$,
MR= the maximum number of sample points on the outermost circle (in pixels),with $MR = INT(2\pi L) + 1$,
NR = the total number of sample points on the outermost circle (in pixels), with $NR \leq MR$.

So, the first step is the evaluation of the centroid *O* of the silhouette of the object under study. The second step lies in the evaluation of the main orientation of the pattern in the 2D space. In the case of industrial parts, sometimes anchor points can be used as a starting point for the sampling process [4,5]. In the case of handwritten signatures, the baseline of the signature is the natural choice for this class of patterns [Figure 6]. These operations can be implemented with the evaluation of statistical moments. Consequently, *invariance in translation* and *in orientation* is obtained by this process.

The third step is to locate the circumscribing circle *C* of the pattern under study. We observed in our database (800 signatures from 20 writers) that the average length of the signatures is around 256 pixels. Let us recall that all images have a format of 128x512 pixels. Now two situations can be considered. *Invariance in scale* can be obtained if the outermost circle of the sampling process corresponds to the circumscribing circle which is automatically adjusted to the silhouette of the pattern [see Figure 6]. In the contrary, we can adjust the outermost circle to a fixed value and let the pattern centered inside the sampling area. In this work both schemes have been studied in a way to evaluate if the difference in aspect ratio between a genuine signature and a random forgery is an important feature in the verification process. Consequently, *OA* is fixed to 256 pixels when invariance in scale is not considered, and this parameter is automatically adjusted to the radius of the circumscribing circle in the other case. The sampling rate on a radius is fixed to *NS*=128 pixels and the corresponding maximum number of sample points on the outermost circle has been settled to *NR*=804. Now, the following parameters can be evaluated easily [Figure 6]. Let

α = the sampling length unit with $\alpha = OA / (NS - 1)$, and
β = the angular step with $\beta = 2\pi / NR$.

The choice of *NS* = 128 has two main consequences. The first one is that all signatures with a length below or

equal 256 pixels will be oversampled in the situation where NS=MS=128; here all original information will be keep after the sampling process. For signatures with their length in the range of values between 256 and 512 pixels ($NS < MS$), the oversampling will be less important. In both cases, the oversampling phenomena is more important near the center area.

3.2 Similarity measure between two Shape Matrices

The evaluation of the similarity between two SMs is a very simple process too. Each location (i,j) of a SM has a value 0 or 1. The task consists in the comparison of the binary values at locations (i,j) of two SMs for all $0 <= i < NS$ and $0 <= j < NR$ and to compute :

cp = the number of corresponding black sampling points between two shape matrices,
ca = the number of corresponding white sampling points between two shape matrices,
nc = the number of non-corresponding sampling points between two shape matrices.

At the end of the comparison process, a similarity measure is easily obtained [4-6]:

$$S_A = \frac{cp + ca}{cp + ca + nc}, \text{ with } 0 \le S_A \le 1.$$

The problem with similarity measure S_A is that the value of term ca is normally very high when the class of signature (line) images is considered. The term ca produces a bias in the evaluation of the similarity between two SMs and this is why a new definition is proposed for this class of images :

$$S_B = \frac{cp}{cp + nc}, \text{ with } 0 \le S_B \le 1.$$

Similarity measure S_B takes into account all corresponding black pixels (cp) and the non corresponding one (nc), but the background is not considered in the definition of the similarity between two SMs. This new definition is more suited to the interpretation of line images where the background is very important in the field of view of the sampling area. Consequently the elimination of term ca gives a better dynamic range for the measure S_B and the discrimination power is more relevant.

In a way to cope with the bias (redundancy) introduced by the *oversampling phenomena*, Taza and Suen [5] make use of a weighting factor defined as :

C_i = the circumference of a given circle i (in pixels),
R_i = the sampling redundancy for a given circle C_i,

$$R_i = NR / C_i, \text{ with } 1 \le i < NS$$

W_i = weighting factor , $W_i = 1 / R_i$,$1 \le i < NS$ with $W_0 = (NS - 1) / NR$.

Here, NS = 128, NR = 804 with OA = 256 pixels when invariance in scale is not considered; otherwise OA is proportional to the length of the signature. Now, the similarity measure between two SMs can be reformulated based on the use of weighting factor W_i in the comparison process. Let

wcp = the weighted sum of W_i related to corresponding black sampling points between two SMs,
wca = the weighted sum of W_i related to corresponding white sampling points between two SMs,
wnc= the weighted sum of W_i related to non-corresponding sampling points between two SMs.

The weighted sums are computed for all locations (i,j) with $0 <= i < NS$ and $0 <= j < NR$. Then, similarity measures S_A and S_B become :

$$S_1 = \frac{wcp + wca}{wcp + wca + wnc}, \text{ with } 0 \le S_1 \le 1$$

$$S_2 = \frac{wcp}{wcp + wnc}, \text{ with } 0 \le S_2 \le 1$$

4. Experimentation

The new similarity measure has been evaluated following our standard experimental protocol and database [1,2]. A minimum distance classifier with threshold has been used with 6 reference signatures. All experimental results are shown in Tables 1 and 2 where $\varepsilon_t = (\varepsilon_1 + \varepsilon_2)/2$ represents the mean total error rate evaluated for all the writers enrolled to the verification system. Let us recall that ε_1 represents the percentage of genuine signatures rejected by the system, and ε_2 shows the percentage of random forgeries accepted by the verification system.

Case I: No preprocessing

In this experiment, the effect of weighting and this one related to scale invariance have been evaluated using binary images without preprocessing. It is clear that the new similarity measure works better than this one proposed in [4,5]. We can observe the following results from the analysis of related numerical values :

Weighting and scale invariance have no effect at all when the classical similarity measures (S_A or S_1) are used ($\varepsilon_t \approx 20\%$).

New similarity measure S_B with scale invariance outperforms the older one (S_A) without the weighting mechanism ($\varepsilon_t = 20.94\% \Rightarrow \varepsilon_t = 7.07\%$) and the latter improve greatly the performance of the similarity measure ($\varepsilon_t = 7.07\% \Rightarrow \varepsilon_t = 2.95\%$).

Finally, based on the weighting mechanism and on similarity measure S_2 it is obvious that better results have been reach without scale invariance ($\varepsilon_t = 1.91\%$).

Case II: Preprocessing without weighting

The goal of this experiment was to compare both similarity measures S_A and S_B in a way to evaluate the influence of all preprocessing schemes on the performance of the verification system. We can resume the experimental results by [Tables 1 & 2] :

Using classical similarity measure S_A, it is obvious that all preprocessing algorithms made a nice improvement in term of experimental results when scale invariance is considered. Moreover, more improvements were obtained based on the envelope of the silhouette of the signature. In brief, error rates were dropped from $\varepsilon_t = 20.94\% \Rightarrow \varepsilon_t = 8.47\%$ when preprocessing is applied to the signature images.

Using again similarity measure S_A without scale invariance, little improvement has been reach in the case of smearing with $\varepsilon_t = 6.90\%$ which is the best result obtained with this similarity measure.

Based on new similarity measure S_B, the impact of preprocessing is not very important whenever the invariance in scale is considered or not. Globally, better results were obtained without scale invariance in all situations. The improvement obtained in the situation where the envelope of the signature is considered instead of using the original binary images is not so evident with $\varepsilon_t = 6.87\% \Rightarrow \varepsilon_t = 5.27\%$.

Case III: Preprocessing with weighting

The effect of the weighting mechanism improve dramatically the performance of both similarity measures, but the new one outperform greatly the older one. Moreover, it is clear from Tables 1 and 2 that the performance is better without scale invariance in all situations. The key points resulting from a deep analysis of experimental results in the best situations without scale invariance are described now.

In the case of classical similarity measure S_1, all preprocessing schemes made a clear improvement of the verification system as in the situations observed with similarity measure S_A. Moreover, the experimental performance was improved greatly based on the use of the smearing algorithm instead of original binary images with $\varepsilon_t = 12.23\% \Rightarrow \varepsilon_t = 2.43\%$.

With the new similarity measure S_2, it is interesting to note that the effect of all preprocessing algorithms on the performance of the verification systems is not very important considering that we can observe $\varepsilon_t = 1.91\% \Rightarrow \varepsilon_t = 0.84\%$.

5. Conclusion

A new similarity measure between two shape matrices has been proposed in this paper. This similarity measure seems very well suited for the interpretation of the class of signature (line) images. This approach outperform all global shape factors designed and evaluated on the same database [2] and experimental results reach those one obtained with local approaches [1].

6. References

[1] Sabourin R. and Genest, G., "An Extended-Shadow-Code Based Approach for Off-line Signature Verification: Part -I- Evaluation of The Bar Mask Definition", *12th ICPR*, Jerusalem, Israel, October 9-13, Vol II, 1994, pp. 450-453.

[2] Drouhard, J.P., Sabourin, R. and Godbout, M., "A Neural Network Approach to Off-Line Signature Verification Using Directional PDF", Pattern Recognition, Vol 29, No 3, March 1996, pp 415-424.

[3] Cheriet,M. et al. "Background Region-Based Algorithm for The Segmentation of Connected Digits", 11th ICPR,The Hague, The Netherlands, Aug 30 - Sep 3, 1992, pp 619-622.

[4] Goshtasby, A. "Description and Discrimination of Planar Shapes Using Shape Matrices", IEEE Trans. on PAMI, Vol. PAMI-7, No. 6, nov. 1985, pp 738-743.

[5] Taza, A. and Suen, C.Y., "Discrimination of Planar Shapes Using Shape Matrices", IEEE Trans. on SMC, Vol. 19, No. 5, sept-oct 1989, pp 1281-1289.

[6] Sabourin, R., "Choix d'un Facteur de Forme Basé sur l'Utilisation des Matrices d'Échantillonnage Polaire (MEP)", Conf. et Expo. sur l'Automatisation Ind., Montréal, juin 1992, pp 20.21-20.25.

Table 1: Experimental results (ε_t in %)

With Scale Invariance				
Preprocessing	Without weighting		With weighting	
	S_A	S_B	S_1	S_2
No	20.94	7.07	19.37	2.95
Loop Filling (LF)	12.90	6.67	9.84	2.38
Smearing	8.83	6.12	4.43	1.88
Smearing + LF	8.69	8.32	4.06	2.66
Closing + LF	8.47	5.47	4.52	1.96

Table 2: Experimental results (ε_t in %)

Without Scale Invariance				
Preprocessing	Without weighting		With weighting	
	S_A	S_B	S_1	S_2
No	20.48	6.87	19.23	1.91
Loop Filling (LF)	13.17	6.41	10.68	2.03
Smearing	6.90	5.33	2.43	**0.84**
Smearing + LF	7.09	7.57	2.57	1.34
Closing + LF	7.86	5.27	4.74	1.57

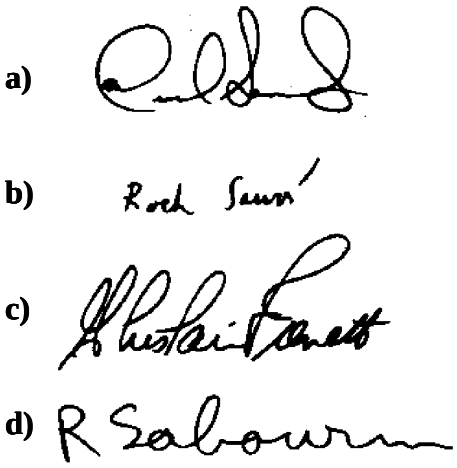

Figure 1

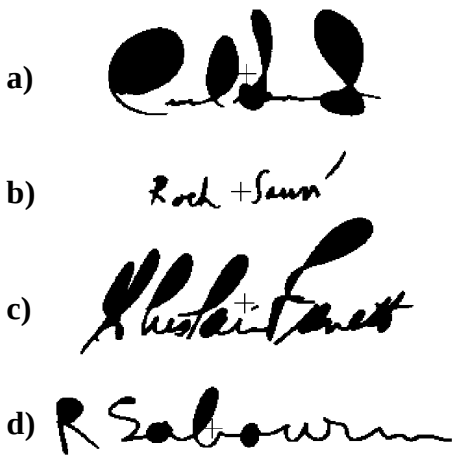

Figure 2

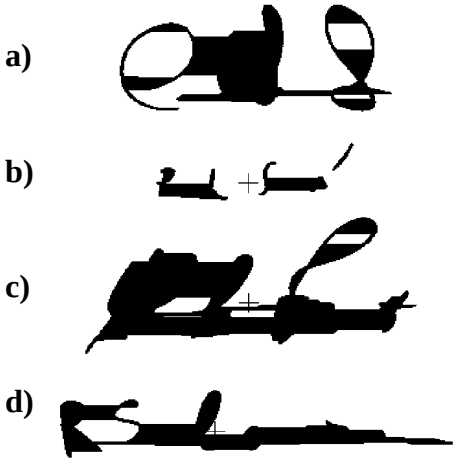

Figure 3

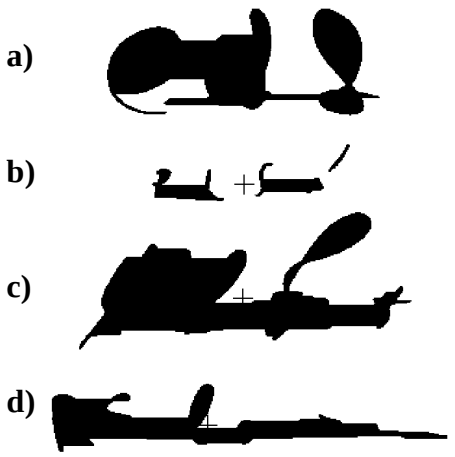

Figure 4

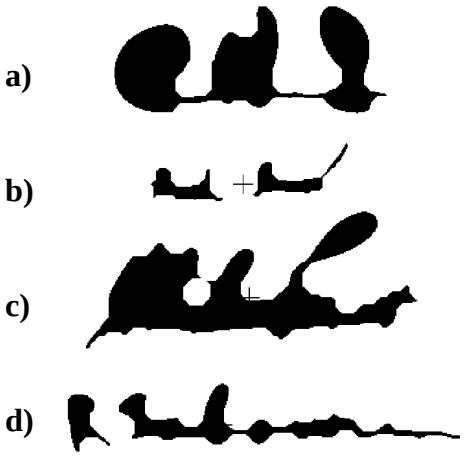

Figure 5

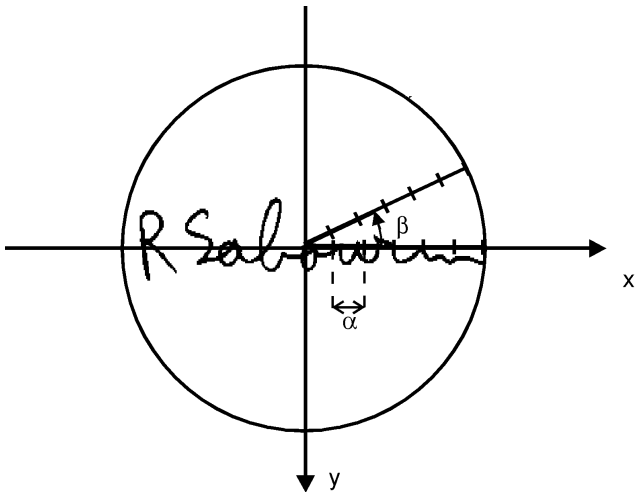

Figure 6