A Hybrid On/Off Line Handwritten Signature Verification System

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Abstract

This paper proposes a new hybrid handwritten signature verification system where the on-line reference data acquired through a digitizing tablet serves as the basis for the segmentation process of the corresponding scanned off-line data. Local foci of attention over the image are determined through a self-adjustable learning process in order to pinpoint the feature extraction process. Both local and global primitives are processed and the decision about the authenticity of the specimen is defined through similarity measurements. The global performance of the system is measured using two different classifiers.

1. Introduction

Signature verification systems are usually built following either on-line or off-line approaches, depending on the kind of data and application involved. On-line systems generally present a better performance than the off-line ones but require the necessary presence of the author during both the acquisition of the reference data and the verification process limiting its use certain kind of applications [1,2,3]. Off-line systems generally don't require the use of any complex apparatus rather than a simple scanner but usually require a more complex or refined preprocessing step, generating also a greater database size [1,2,3].

In this work a hybrid on/off line signature system was developed, limiting the use of a digitizing tablet to the acquisition of the reference data. The verification process can be done directly over the desired document, without the necessary presence of the author of the signature. The on-line reference data serves as a basis for the localized feature extraction process and for segmenting the off-line test data to be acquired during the verification step.

The system processing can be divided essentially into two modules: The acquisition and training module (on/off-line), and the verification module (off-line). The first module is responsible for the processing of the on-line reference data, generating the thresholds needed during the verification step. The second module inputs the test image to the system, extracting similarity measurements between the reference and the test data and reaches a verdict about the authenticity of the signature.

This kind of hybrid system could be easily adapted to be used on a banking environment where the presence of the customer is needed to open a new account , but is unnecessary during the verification of the signature in checks and other documents.

The next two sessions describe in detail each of the modules. In Session 4 the experiments and results are presented, followed by the conclusion and comments on Session 5.

2. On-Line/Off-Line Hybrid Module

This module of the system is composed by six processing steps, responsible for the acquisition and treatment of the on/off-line data as follows.

Step 1: Acquisition: The reference signature data is read with the help of a digitizing table in order to gather the dynamics and the image of the signature (Figure 1). The number of signatures per author read depends on the desired system performance (see Session 4 for details).

Step 2: Preprocessing: The input data is filtered by a low-pass filter in order to eliminate spurious noise inherent to the acquisition process [4], and it is pre-segmented into strokes produced by pen-up/pen-down movements.

Step 3: Recursive sampling: A skeleton of the signature is generated by recursive sampling of the resulting points by splines [5] (Figure 2).

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Step 4: Segmentation into strokes: The skeleton is segmented according to the complexity of the underlying strokes [6]. The segmentation is done based on curvature changes (constant/variable), inspired on a psycho-physical delta-lognormal handwritten reproduction model [7]. The calculus of the curvature is done by the DOS method (differences of slopes) [8]. The regions formed serve as a basis for the creation of local windows – or foci of attention - over the signal in order to localize the feature extraction process (Figure 3).

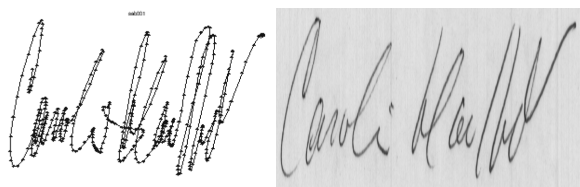

Figure 1 - On-line and off-line data samples.

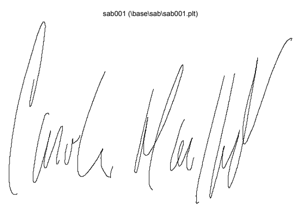

Figure 2 - Filtered/sampled signature skeleton.

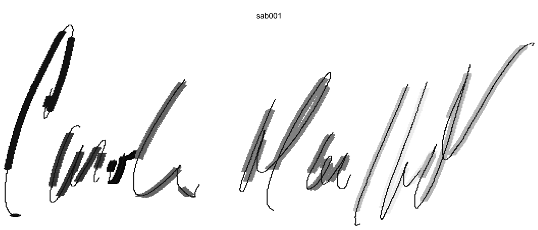

Figure 3 - Segmented signature according to the stroke complexity (thick lines correspond to simple strokes).

After this step the skeleton of the dynamic data is completely segmented and will be used as a framework for segmenting the correspondent image of the signature.

Step 5: Windowing: Windows are created around the simple stroke regions, following the general outline of the strokes. The length of the window is equal to the length of the correspondent simple stroke. The exact width of those windows will be determined during the learning process to follow.

In order to accomplish this task, the skeleton and the original image have to be overlapped. The operation is done initially through a resolution change in order to equalize the different resolutions (as described in Section 3) and by centering both from their respective center of gravity.

The center of gravity of the image is calculated by first eliminating the foreground through a threshold operation [9] over the histogram of the gradient, calculated by a Sobel mask operator [10], and then by using the pixel intensity values as weights.

The result of those operations can be seen on Figure 4. Generally the overlapping procedure is not perfect due to rounding errors but the differences will be compensated during the learning phase ahead.

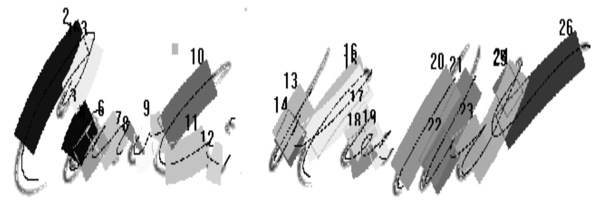

Figure 4 - Windowing process of the image.

Each window region is now individually labeled forming an envelope around the signature and can be easily accessed during the local feature extraction process.

Step 6: Learning: This step is responsible for adjusting the size of each of the simple stroke window region, choosing at the same time a representative prototype signature among the reference data. This will be done by a process aiming at reducing the within-class distance between any given pair of reference signatures acquired. The resulting signature skeleton with its personalized windows envelope will be used during the verification module of the system. Meanwhile the mean and standard deviation of all local and global features used by the system are computed in order to be fed later into the classifier. They are as follows:

Global Features:

- - The aspect ratio of the signature, calculated by the ratio of the standard deviation of the pixels in relation to the center of gravity of the signature on both X and Y axes.
- - The proportion of pixels localized outside the rectangle formed by the standard deviation of the pixels previously determined.
- - The slant of the signature.
- - The distribution of the pixels around the X and Y axes (standard deviations).

Local Features:

- The overall direction of each stroke represented by the circular mean of the directional probability density function calculated over each window.
- The proportion of pixels inside each window over the total number of pixels.

The direction of each individual signature stroke plays a fundamental role in the proposed learning process. It will be obtained by the circular mean [12] of the directional probability density function [13] calculated over the pixels of the previously segmented windows.

The distance between a given pair of reference signatures is calculated as the total difference of direction of each individual stroke of the signature. A small distance represents a great similarity between both signatures.

The reference signatures are analyzed in pairs, with the envelope of one signature overlapping the image of another. For a three reference set this represents a total of 6 possible combinations.

For any given two reference signatures *S1* and *S2*, the learning process is as follows:

1. Initially the fixed width window envelope of *S1* (generated previously) is put on top of the image of the same *S1* signature in order to calculate the mean direction of its individual strokes for the given window size configuration, producing $\bar{\theta}S1_1 \, \Lambda \, \bar{\theta}S1_n$, where n is the number of windows.
2. The envelope of *S1* is now put over the image of the second signature *S2*, and the corresponding $\bar{\theta}S2_1 \, \Lambda \, \bar{\theta}S2_n$ mean directions are calculated.
3. The total distance between both signatures is determined as:
$$DistS1S2 = \sum_{i=1}^{n} \sqrt{\left(\bar{\theta}S1_i - \bar{\theta}S2_i\right)^2}$$
4. The width of the first window is changed and steps 1 to 3 are repeated. If the new calculated distance is smaller than the previous one, the new window size is kept in place of the older one. If not, the original width remains. Step 4 is repeated for the entire range of desired width values for each window. Experiments were done using several different ranges and the values of 80, 100 and 120 pixels worked the best for the size of signatures available. So in this case, Step 4 is to be repeated three times for each window of the envelope.
5. The result of step 4 above will be a customized envelope that generates the minimal distance between the two signatures *S1* and *S2*. Next, another pair of envelope/image is selected and the process repeats itself until there are no more combinations available.

After the training there will be a set of optimized distance envelopes for all of the reference signatures. In order to allow within-class variations, the signature that presents the maximum calculated distance among the optimized envelopes will be chosen as the prototype that will represent all the signatures of the class.

After the learning process the images of reference signatures can be discarded and only the envelope and the thresholds (standard deviation and mean of the extracted features) will be saved in the database.

3. Off-Line Module

The off-line module will process the image of the test signature, comparing it against the reference data.

Step 1: Acquisition: The test signature image is read with the help of digitizing equipment such as a scanner.

Step 2: Preprocessing: The input data is filtered in order to extract it from the background using the same threshold operation described elsewhere. Depending on the application, other operations might be needed in order to eliminate horizontal lines and/or drawings from the image but they are not addressed in this work.

Step 3: The correspondent window-formed skeleton is extracted from the database and is put over the image of the test signature (Figure 5).

Step 4: The extraction of the local and global features takes place, delimited by the windows of the reference skeleton.

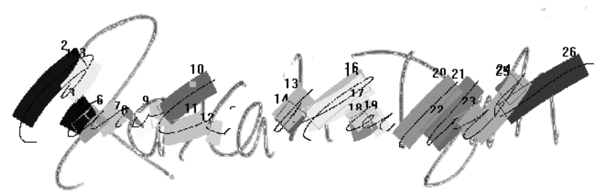

Figure 5 - Feature extraction: The windowed reference of the prototype is put over the test image.

Step 5: The decision over the authenticity of the test image is taken upon the comparison between the local and global features extracted versus the thresholds stored during the learning phase.

4. Experimental Results

The first on/off-line database used was made of 400 signatures, with 20 signatures per writer (20 writers). The online data was acquired through a digitizing tablet at a sampling rate of 100Hz and a resolution of 1000 dpi. Each sample is formed by a three number set. The first number indicates the proximity of the pen to the surface of the tablet and the next couple represents the *x,y* coordinates relative to the upper left hand corner of the instrument. The authors were instructed to write over a framed white sheet of paper placed on top of the tablet to produce the corresponding off-line data. The images were

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then scanned at 300 dpi (using grayscale) in order to form the off-line database.

A second off-line only database was formed containing 500 signatures from 50 other writers (10 signatures per person), also scanned at 300 dpi.

Three kinds of experiments were produced. In the first and second experiments the performance of the system was tested by the use of multiple Euclidean Distance classifiers working on a vote scheme. The third experiment works with a single Euclidean Distance classifier, where the similarity measurement is done over the addition of all the distances produced by the individual features.

The first experiment is divided in two parts. In the first part three randomly chosen signatures per writer were used as reference and the remaining 17 were used as test. Random forgeries were tested by using the remaining writer's signatures. In the second part five randomly chosen signatures were used as reference, with the remaining 15 used as test. The performance of the vote-based classifier was evaluated. If the value of a given feature was within the desired threshold calculated during the learning phase, a favorable vote was issued. The number of votes issued by all the seven processed features determined the acceptance or refusal of the signature. Table 1 shows the equal error rate (EER) produced by the classifier using three and five reference signatures. The number of votes shown indicates the limit considered in order to accept a signature as authentic. Figure 6 shows the FRR/FAR curves for 3 and 5 reference signatures and the decision threshold of 5 votes.

In the second experiment the 500 unseen signatures from the second image-only database were used as random forgeries instead of the remaining signatures of the first database. The performance of the same vote based classifier working with three and five reference signatures is assessed. Table 2 shows the verification results for this database.

Table 1 - Signature verification results – first database.

Number of reference signatures	% EER for: 4 votes	5 votes	6 votes
3 signatures	8,97	8,54	9,84
5 signatures	7,21	5,30	5,53

Table 2 - Signature verification results – second database.

Number of reference signatures	% EER for: 4 votes	5 votes	6 votes
3 signatures	8,19	7,77	8,33
5 signatures	6,33	4,20	4,67

On the third experiment, the first database is used again to assess the performance of the system working with all the seven features together, using this time 3, 5 and 10 reference signatures (see results on Table 3). Figure 7 shows the FRR/FAR curves for 5 and 10 reference signatures.

Table 3 - Signature verification results - first database.

Euclidean Dist. Classifier (%EER)	3 references	5 references	10 references
	10,8	5,16	1,19

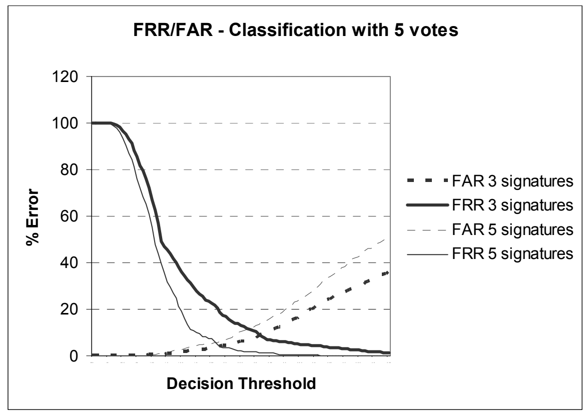

Figure 6 – FRR/FAR curve for the vote-based classifier working with the first database and a decision threshold of 5 votes.

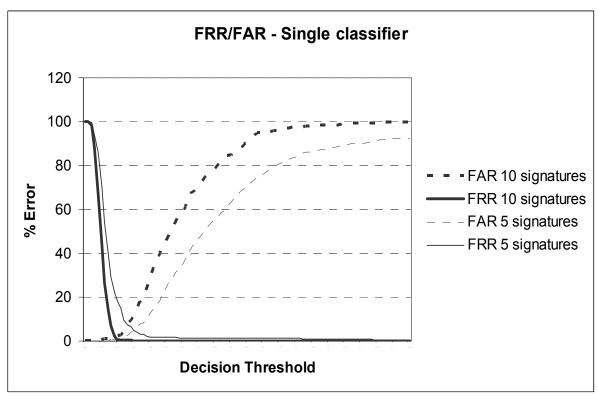

Figure 7 - FRR/FAR curve for the single Euclidean Distance classifier working with the first database.

5. Conclusion

Practical signature verification systems are hard to be developed. On-line systems have good performance but cannot be used to verify bank checks and documents in general since they need the dynamics of the signature. Off-line systems have poorer performance and usually require a large database space. In this work a new on/off line hybrid system was proposed where the acquisition of the data is done by a digitizing tablet but only the image of the test signature is needed during the verification process. Instead of a well known off-line grid-like segmentation [11], a window-focused segmentation process was suggested. The on-line segmentation was done according to the complexity of the underlying strokes [6], inspired by a psycho-physical handwritten reproduction model [7] and is used to limit the local feature extraction process.

Results indicate that there is much room for improvement. Although not yet satisfactory, equal error rates of about 5% for 5 reference signatures and about 1% for 10 reference signatures could be achieved by the use of common Euclidean Distance measurements. As a future work, further improvement on the learning process with the introduction of new metrics and the inclusion of complex strokes on the analysis of local features are viable options.

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