Off–Line Signature Verification Based on Feature Matching

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Off-Line Signature Verification Based on Feature Matching

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Abstract-This paper presents a novel approach for off-line signature verification. First the different aspects and problems of signature verification are discussed in conjunction with off-line analysis methods. It is shown, that on-line analysis methods perform usually better than off-line methods because they can make use of the temporal information (and thereby get a better perception of the semantics of the signature). An assumption is made, that off-line verification methods have difficulties improving their results because of the high level of abstraction they use, which is a direct consequence of the missing semantics. Afterwards a solution is presented with the ability to preserve some semantic information, and thereby deliver a better ability to analyze the results and optimize the system.

I. Introduction

Signature recognition is probably the oldest biometrical identification method, with a high legal acceptance. Even if handwritten signature verification has been extensively studied in the past decades, and even with the best methodologies functioning at high accuracy rates, there are a lot of open questions. The most accurate systems almost always take advantage of dynamic features like acceleration, velocity and the difference between up and down strokes. This class of solutions is called on-line signature verification. However in the most common real-world scenarios, this information is not available, because it requires the observation and recording off the signing process. This is the main reason, why static signature analysis is still in focus of many researchers. Off-line methods do not require special acquisition hardware, just a pen and a paper, they are therefore less invasive and more user friendly. In the past decade a bunch of solutions has been introduced, to overcome the limitations of off-line signature verification and to compensate for the loss of accuracy. Most of these methods have one in common: they deliver acceptable results but they have problems improving them.

II. Related work

The biggest limitation of off-line signature verification methods is the absence of temporal information. In the on-line case this can be used, to segment the signature in a semantically meaningful way and even to define an unambiguous matching between the parts of two signatures. In the off-line case no definite matching exists. These methods can only operate on static image data; therefore they often try to compare global features like size of the signature or similarities of the contour [1] [2] [3]. To get a tractable abstraction of the two dimensional images, these methods often involve some image transformation, like the Hough or Radon transformations [4] or work on the density models of the signatures [5]. Although these methods almost totally ignore the semantic information hidden in the signature, combined with each other they seem to give a good representation of the signature, allowing the researchers to reach Equal Error Rates (EER) between 10% and 15% [6]. The drawback of this methodology is that loosing the semantic information makes it almost impossible to improve the algorithm or to explain the results in detail. Jose L. Camino et al. take an other approach [7] they try to guess the pen movements during the signing by starting at the left and bottom most line-end and then following it. There are also other approaches trying to reconstruct the signing process. In [8] stroke, and sub-stroke properties are extracted and used as a basis for the comparison. Based on own experience, these latter approaches seem to be the most promising, because their results can be explained (and therefore improved) in a semantically meaningful way.

There is also a wide variety of classifiers used to compare the results: hidden Markov models [7] [9], Support Vector Machines [4], multi-layer perceptron [10], genetic algorithms, and neural networks [11] are the most widely used solutions.

III. Signature Processing

The majority of signature verification methods can be divided into five main phases: data acquisition, preprocessing, feature extraction, processing and classification (although these steps are not always separable nor they always follow the same chronological order). In the off-line case data acquisition means simply the scanning of a signature. This is followed by preprocessing whereby the images of signatures are altered (cropped, stretched, resized, resampled etc.) to create a suitable input for the next phase. The next step is feature extraction, the process of identifying characteristics, which are inherent to the particular person. The processing phase is mainly based on a single comparison algorithm, which is able to calculate the distance function between signature pairs. Using these results,

the classification phase is able to make a decision, whether to accept or reject the tested signature.

A. Preprocessing

Signatures are scanned with 600dpi resolution, resulting in an average image size of 1000*250 pixels. This resolution has shown to be necessary to correctly interpret the line crossings.

Signature preprocessing is a necessary step to improve the accuracy of the latter algorithms, and to reduce their computational needs. The following steps are done:

1.) A *noise filter* is applied to remove the noise caused by the scanner.

2.) The image is *cropped*, to the bounding rectangle of the signature.

3.) Transformation *from color to grayscale*, and finally to black and white.

4.) *Thinning* the black and white image results always in a huge information loss. Therefore it is essential to select a thinning algorithm which gives a good abstraction of the original signature, with a low noise level. We selected an algorithm, which removes pixels so that an object without holes shrinks to a minimally connected stroke, and an object with holes shrinks to a connected ring halfway between each hole and the outer boundary [12].

B. Feature Extraction

Once, the preprocessing has finished, the endpoints of strokes are identified. These are pixels with one single neighbor connected. To help improve the robustness of the latter processing algorithms, endpoints are also characterized by the direction of their corresponding strokes. Direction vectors are calculated from the first 10 stroke pixels next to the attached endpoint (Fig. 1). Connections are defined in a similar way except that they have 3 directions associated with them (Fig. 2).

There are two side effects of the thinning algorithm which should be noted here.

1.) Rapid changes in pen angle often result in falsely detected endpoints. Although this reduces the quality of our "abstraction" but it does not reduce the quality of our matching algorithm because such changes in angle are as characteristic as real stroke endpoints.

2.) Connection points will always have three branches. This property only simplifies our mathematical model.
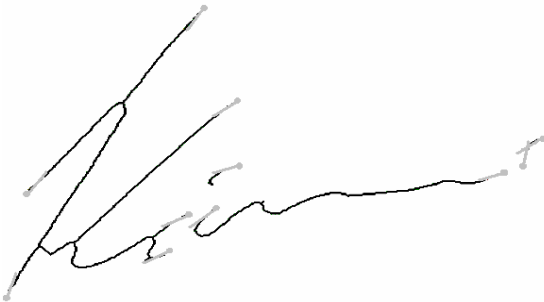

Fig. 1. Endpoints are represented by their location and direction

Fig. 2. Connections are represented by their position and 3 directions

IV. MATCHING OF SIGNATURES

In this section the algorithms that were used to match the features of the signatures are discussed.

A. The Dynamic Time Warping (DTW) algorithm

The DTW algorithm [13] takes two signals and returns a measure of the dissimilarity of these signals. It is a dynamic programming method used to obtain a nonlinear transformation between two signals.

Given

$$S_1 = (P_1(1), \ldots, P_1(T_1)) \quad \text{and} \tag{1}$$

$$S_2 = (P_2(1), \ldots, P_2(T_2)) \tag{2}$$

signals with P points, additionally

$$D(S_1, S_2) \tag{3}$$

distance function. The DTW finds a warping function

$$\phi = [\phi_1, \phi_2]^T, \tag{4}$$

that minimizes the dissimilarity between S_1 and S_2:

$$\phi = \arg\min_\phi D(S_1, S_2) \tag{5}$$

with the following recursion:

$$D(t) = \min_{\phi_1(t-1), \phi_2(t-1)} \left\{ D(t-1) + d \begin{pmatrix} (P_1(\phi_1(t-1)) P_2(\phi_2(t-1))), \\ (P_1(\phi_1(t)) P_2(\phi_2(t))) \end{pmatrix} \right\}$$

where

$D(t)$ is the cumulated distance up to step t

$D(t-1)$ is the cumulated distance up to step $t-1$

$d(\ldots)$ is the elementary distance between matched points

Note, that there is a 2D variant of the DTW algorithm in the literature, and it was applied to signature analysis. We used the 1D case to match the top and bottom edges of the signatures. This could be enhanced with a contour tracking method.
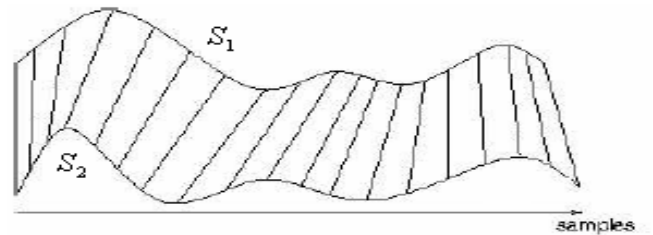

Fig. 3. Comparison of two curves using Dynamic Time Warping.

B. Mutual Information Algorithm

The features extracted in III.B have both position and orientation information. A new algorithm (Mutual Information Algorithm (MIA)) is proposed, which takes all these properties in consideration.

This is done through the following metrics:

absolute distance from an appropriate reference point
orientation of the above distance vector
and the *own properties* of the features (at the endpoints this is *angle* compared to horizontal axe, at junctions there are *three angles* compared to the horizontal direction, etc.)
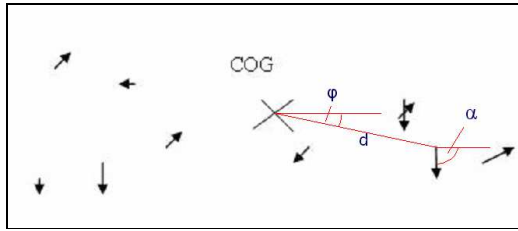
Fig. 4. Properties of the features (the arrows represent the position and orientation of endpoints in a signature).

The first two represent the localization information, the third is the own information of the feature. While the localization is global information, the features own properties are locally determinative.
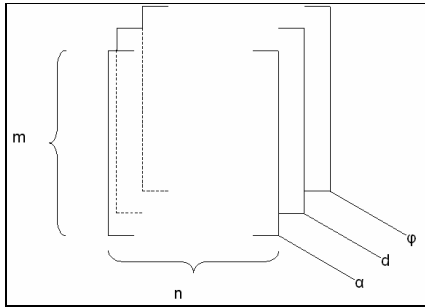
Fig. 5. Differential matrix of the properties, where one of the signatures has 'm' and the other one has 'n' features.

The algorithm runs cyclically (like the Iterative Closest Point algorithm), because the reference point is changed in every loop. For the first iteration, the appropriate reference point could be simply the center of gravity (COG) in both images. The angles were calculated in radian, and quadratic distances were used. These values are scaled into the [0,1] interval, and they are weighted with the same price in the first examinations. This could be improved, by using different weights for these measures..
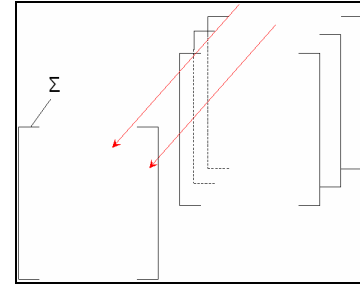
Fig. 6. Addition of the differential matrix

Values are added and sorted by the results. In the next loops new reference points are selected to refine the order. The features with the smallest distance are selected from each image respectively to be used as reference points in the next iteration
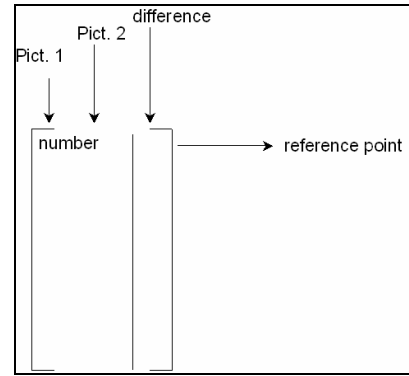
Fig. 7. Selection of the reference point in the second loop

During the processing the results are accumulated. In every loop, the multidimensional differential matrix is extended by new dimensions.
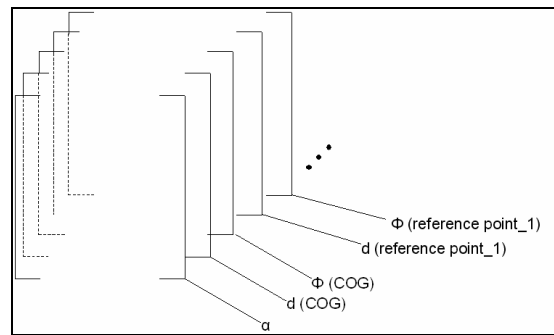
Fig. 8. Extension of the differential matrix's dimensions

Finally a list of the corresponded features in the images is obtained. Based on our observations the true corresponded ones are located at the top of the list, while the end of the list contains mainly mismatches. A threshold (Threshold_1) must be defined to separate the significant high differential levels.

Then a second threshold (Threshold_2) has to be selected to decide whether the signature is an original or a forgery.
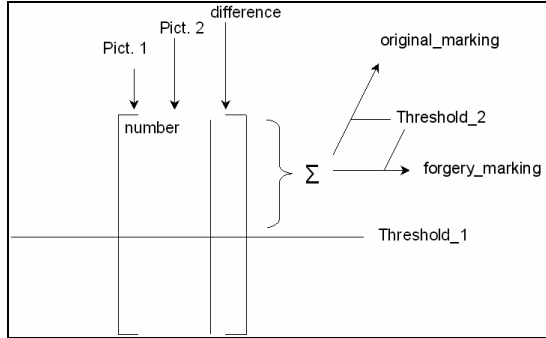

Fig. 9. the thresholds of the decision.

In optimal case a number of original signatures are available to verify the identity of one single signature. In this case it can also be decided, whether the analyzed signature is original or not by a simple voting mechanism (majority decision).
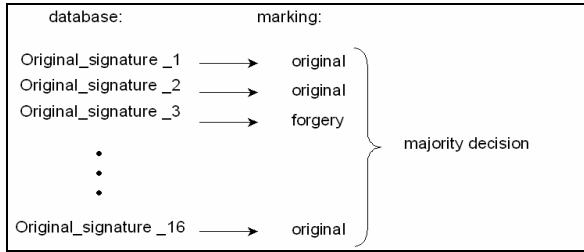

Fig. 10. Majority decision

V. EXPERIMENTAL RESULTS

A signature database is a set of digitalized signatures (mostly scanned images) from a set of subjects. Algorithms are developed and evaluated with, and tested against this database. As a common practice, the database is divided into a training set and a validation or test set thereby eliminating the direct influence of the learning process on the verification process. A database can be characterized by the number of signers, and the number of signatures. Signatures can be divided into further groups. There are original signatures (signatures belonging to their signers), simple forgeries (imitations of the signature of the original signer, but without a priori knowledge of it) and skilled forgeries (created after studying the original signatures). Some algorithms use random forgeries which can be derived from the previous sets.

In our experiments 16 original signatures were taken from 50 different signers. Then some of the signers were requested to stay and create forgeries of the original signatures, 16 pieces for every person. 640 signatures (320 originals and 320 forgeries) from 20 signers were used to tune our algorithm, and the other 960 signatures were reserved for benchmarking purposes.

The effectiveness of a system is most commonly described with its "false rejection rate" (FRR, Type I error), its "false acceptance rate" (FAR, Type II error), and the "equal error rate" (EER). The false rejection rate is the percentage of original signatures the system rejects. The false acceptance rate is the percentage of forgeries the system accepts as original, and the equal error rate is the point at which the two factors intercept.

Using our benchmark database, we were able to achieve an EER value of 20.5 %. For some other configurations, see Fig. 11.

VI. CONCLUSION

A novel signature verification method was introduced, which is able to preserve and take usage of semantic information during signature comparison. Experimental results are promising, even now, when the algorithm uses only a fragment of this semantic information. Further benefits of this approach are, that each decision made by the algorithm, can be directly interpreted by humans, which facilitates the improvement and debugging of the whole system [14].

Therefore future development will mainly focus on the extraction and comparison of further features. Splines could be fit to the matched points and an appropriate metric could be found to measure the differences of the curves. Our experiences show that tremor is a very typical feature for forged signatures. This tremor could be measured using a Fourier transformation for calculating the distance from the smoothed curves. The endpoints could be also extended by a new metric, describing the runoff of the corresponding stroke. These runoffs could be characterized by the changes in the intensity. Threshold values in our system could be refined by loading the results from the different feature evaluations into an expert system.
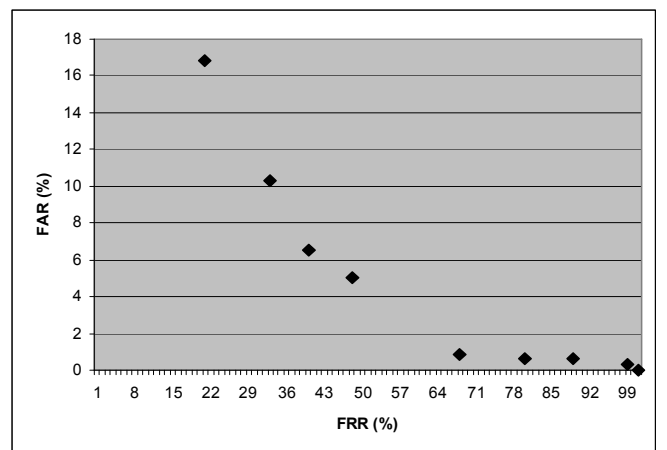

Fig. 11. Experimental results with different threshold configurations

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