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SIGNATURE IMAGE RECOGNITION BY SHAPE CONTEXT IMAGE MATCHING

This paper presents experiments on recognition of signature images. In preprocessing stage a thinning algorithm is used followed by a sampling technique. Sampled points are used to calculate shape context histograms and based on their values corresponding pairs of points from reference and tested signature objects are selected. A distance measure based on shape contexts is used to classify analysed signatures.

1. INTRODUCTION

Handwritten signatures have been widely used for people authentication since many years ago. Even today, when more secure and reliable techniques like digital certificates are available, handwritten signatures play an important role in our lives. Automatic verification of signatures is an active research area [1,3,6,8,10,11,12]. There are also many robust commercial systems capable of detecting even skilled forgery attempts. Most of the systems are on-line based, which means they use dynamic information gathered at the time of signing. This include writing trajectory, timing, velocity, pen pressure and angle. By using this data in the verification process one may achieve very low error rate of signature recognition and high forgery resistance. However, in many situations, such data is unavailable. The signature is usually written on paper without any special equipment to record the dynamics of the signing process. The only available information is the static image of the signature. The off-line systems that analyse this signature image are less reliable and more susceptible to fraud. To improve their performance the recognition algorithms require many genuine and forged samples during training phrase.

In this paper we propose a system that also analyses handwritten signature images but in contrast to previously described off-line systems we constrain the training to one sample per subject. The presented approach may be used for fast signature recognition or identification purpose where there is only one reference signature available.

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2. DATA ACQUISITION

In order to prepare data to the algorithm of recognition, the images of signatures are first stored as Portable Network Graphics files. This format for graphical files provides lossless compression that retains all important features without introducing distortions, and results in relatively small footprint. Images can be obtained by means of scanning devices from original documents. The segmentation of signatures from acquired scans is not considered in this work, but can be easily implemented by applying certain constraints on the position of the signature inside the analysed document. Another problem is noise and defects caused by poor quality of documents and the scanning process. In our experiments we used the threshold technique to eliminate minor distortions and convert images from greyscale into black-and-white binary map. The threshold value is selected experimentally and applied to all signature images. If the value of a pixel in the original image exceeds the threshold it is then converted into a black pixel, otherwise it is treated as a part of the background (white).

3. THINNING

To reduce the amount of information needed to be processed during recognition task the skeleton of a signature image is obtained [5,9,13]. There are many algorithms designed for this purpose. In this work we use KMM method [13]. The KMM algorithm preserves connectivity, produces one-pixel width line and was proved to give very good results for both handwritten script and picture images. Fig. 1 presents examples of signature images and their skeletonized versions obtained by means of KMM algorithm.

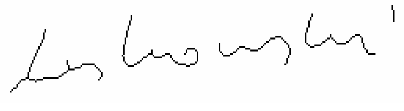
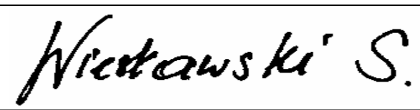
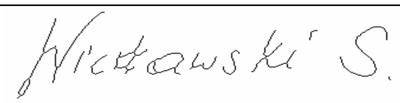
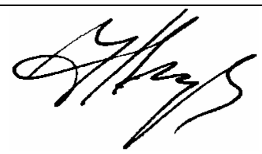
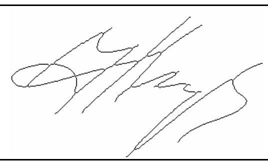
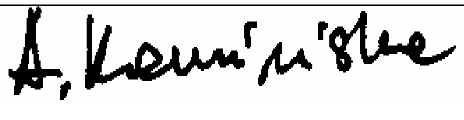
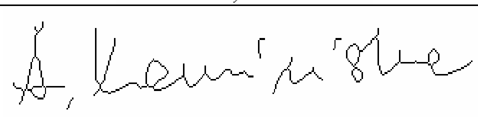
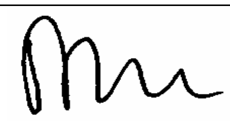
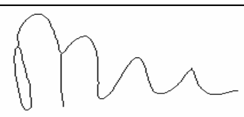
Signature image	**Signature skeleton**
	
	
	
	
	

Fig.1. Signatures and their skeletons obtained by KMM algorithm.

4. SAMPLING

For further reduction of data we use any sampling technique. During the procedure of sampling, we leave N equally spaced points from the thinned signature line, where N is chosen arbitrarily. The sampling algorithm iteratively deletes the signature pixels until only the required number of pixels (N) remains in the image. The signature pixels selected for deletion in each iteration have the smallest distance from their neighbouring pixels. Experiments have shown that a value of $N = 30$ is sufficient to recognize the signature, but for a higher rate of success, the value 50 was given to N (a 92% rate was achieved) or $N = 100$ for about 95% correct recognition. This process is illustrated by Fig. 2 for $N = 100$. Beyond the value $N = 150$, the results had not shown any significant changes or improvement. It was proved and shown experimentally that a higher number of N does not make any advantage concerning the performance. Higher performance with even a less number of points is still our goal. Authors are working on that and some of the results with $N = 30$ are shown below.

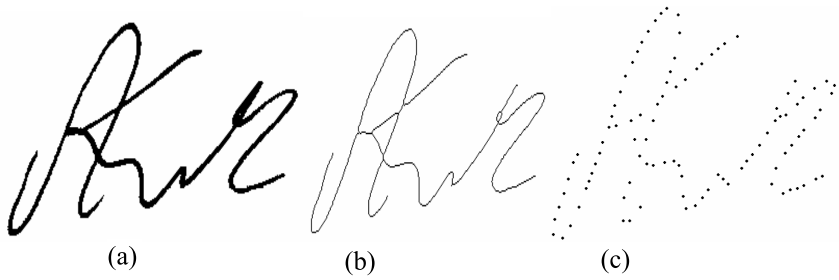


Fig.2. An example of a signature image(a), its skeleton(b) and sampled points(c).

5. SHAPE CONTEXTS

The shape context algorithm [2,7] allows for measuring shape similarity by solving the so called *correspondence problem* [2] between two objects (T, R) and finding an aligning transform. Each of the two objects, whose shapes are compared, is represented by a set of points (1).

$$T = \{t_1, t_2, ..., t_n\},\\ R = \{r_1, r_2, ..., r_m\} \tag{1}$$

For each point on the first object (T) a corresponding point on the second object (R) is found. In order to find corresponding pairs every point is described by a shape context descriptor (2). This descriptor contains information about the configuration of the entire shape relative to the point being described. The shape context descriptor is formed by computing a coarse histogram representing distribution of points comprising the object relative to the reference point. Bins used in the histogram calculation are uniform in log-polar space.

$$h_i(k) = \#\{t \neq t_i : (t - t_i) \in bin(k)\}$$
$$h_j(k) = \#\{r \neq r_j : (r - r_j) \in bin(k)\} \tag{2}$$

The cost of matching two points forming a pair – one point from object T and the other from R can be computed as χ^2 *test statistics* (3):

$$C_{ij} = C(t_i, r_j) = \frac{1}{2}\sum_{k=1}^{K}\frac{\left[h_i(k) - h_j(k)\right]^2}{h_i(k) - h_j(k)} \tag{3}$$

The following step is to find pairs that minimize the expression (4). The result is a permutation P such that the expression (4) is minimized and represents the corresponding pairs of points.

$$H(P) = \sum_i C(t_i, r_{P(i)}) \tag{4}$$

The cost of matching two objects T and R can be computed using equation (5) . In this work it is used as the *distance measure* for signature classification.

$$\cos t(T,R) = \frac{1}{n}\sum_{t\in T}\min_{r\in R} C(t,r) + \frac{1}{m}\sum_{r\in R}\min_{t\in T} C(t,r) \tag{5}$$

The initial estimate of correspondences may contain some errors. In order to improve this estimation iterative process is applied where in each step a transformation function that aligns entire images is constructed [2,7]. In every iteration, before finding corresponding pairs, one of the objects is transformed according to this function and search for pairs is performed using the transformed object's coordinates. This transformation function is computed using the corresponding pairs obtained in previous iteration step by means of regularized thin-plate splines.

6. PREVIOUS STUDIES

In previous studies [1,11,12] we used Dynamic Time Warping (DTW) technique [4] for recognition of signature images. Several methods for characteristic points extraction were tested and used with various modifications of DTW method. Table 1 presents sample results achieved during this study. DTW algorithm presents a measuring tool as a recursive function (6) to compare between two sequences.

$$D(i,j) = \min\begin{Bmatrix} D(i, j-1) \\ D(i-1, j) \\ D(i-1, j-1) \end{Bmatrix} + d(x_i, y_j) \tag{6}$$

The distance measure $d(x_i, y_j)$ can be chosen in various ways depending on the application. In our case, the Manhattan distance was used. The calculations were carried out using dynamic programming. The key part of this algorithm is the computation of cumulative distance $g(i, j)$ as the sum of distance $d(x_i, y_j)$ and one of the cumulative distances found in earlier iterations (7):

$$g(i, j) = d(x_i, y_j) + \min\{g(i-1, j), g(i, j-1), g(i-1, j-1)\} \quad (7)$$

In order to reduce excessive warping of sequences, a constraint is applied that restricts warping paths to a region called "window". The experiments were conducted for various window sizes and modifications to the DTW method.

Table 1. Percentage of properly recognized signatures (DTW method). Columns descriptions : ***P*** – percentage of maximum window's size in DTW method, ***DTW*** – basic DTW algorithm, *DDTW* - Derivative DTW algorithm, ***DTWS*** – basic DTW algorithm with slope constraint.

P	***DTW***	***DDTW***	***DTWS***
10%	74.17%	60.83%	84.17%
30%	74.17%	61.67%	84.17%
50%	74.17%	62.50%	84.17%
70%	75.00%	65.83%	84.17%
90%	78.33%	68.33%	82.50%
100%	64.17%	47.50%	76.67%

7. NEW ANALYSIS

In order to evaluate effectiveness of the method presented in this work several experiments were carried out. The database of signatures was created by 20 different people, with each signature repeated three times, giving a total of 60 signatures. For every person, each of the signatures was used as reference pattern to classify the remaining two. The number of points N sampled from thinned signatures was 30, 50, and 100. The number of 3 iterations was selected for the shape context algorithm. For signature recognition we used *distance measure* based on the shape context cost function given by (5).

Table 2. Percentage of properly recognized signatures (shape contexts method).

Number of samples	30	50	100
Percentage of properly recognized signatures	87%	92%	95%

Table 2 shows the results of recognition. The highest rate - 95% was achieved for signature description consisting of 100 points. The selection of a less samples number decreased the recognition rate, but what is worth mentioning decreasing this number to one third of its value resulted in less than 10% drop of properly recognized signatures. As can be seen the results for shape context technique are better than for DTW distance measure. The size of the feature vector used in [11,12] varied for each of the signatures with the average size of about 60 per signature.

Again, in our study we used only one reference signature per subject which made our task very difficult. Under this constraint achieved results seem to be very promising.

8. COMPARISON WITH OTHER WORKS

A lot of research has been carried out on the signature recognition systems. Most of the approaches can be categorized as follows [15]:

- template matching approach – signature images are compared with templates using image matching techniques,
- statistical-based approach – classification of signatures is based on a set of extracted features and an underlying statistical model using Hidden Markov Models, Bayesian Classification, and others,
- structural based-approach – methods are based on the relational organization of low-level features into higher-level structures usually associated with graph matching techniques,
- spectrum-based approach – decompose a curvature-based signature into a multi-resolution format and analyze it using wavelet theory,
- Neural Networks approach – application of neural networks (usually feedforward using error backpropagation learning algorithm) for recognition of signatures based on extracted features.

The system presented in this work can be categorized into the first class, the template matching approach. The advantage of the proposed method is that by application of context descriptors we can incorporate structural data and utilize information about its relative position in the signature image. This result cannot be achieved by classical known to the authors methods.

Most of the off-line signature recognition systems in the other categories make use of several genuine and forged signatures per subject during the training phrase [14], or select representative reference signature before building the database against which new signatures are tested [8]. In our investigation we used only one reference signature per subject without any prior selection. This may be an important asset in some situations where there is only one genuine signature available for comparison.

9. CONCLUSIONS AND FUTURE WORK

In this work we presented a handwritten signature recognition system The system includes data preprocessing with thinning and sampling methods. The recognition process is conducted by means of a distance measure based on shape contexts descriptors. The achieved recognition rate reached 95% of properly recognized signatures. The system works under constraint of having only one reference signature per subject for training. Future plans include enriching shape context descriptor and incorporating verification phrase.

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