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SIGNATURE VERIFICATION USING CONTEXTUAL INFORMATION ENHANCEMENT AND DYNAMIC PROGRAMMING

This paper presents the results of experiments on online signature verification. Information gathered during the signing process like pen trajectory, pressure, elevation and altitude is utilized to prove the authenticity of a signature or to detect a forgery attempt. Signature verification task is carried out by means of the Template Matching approach. The presented method is based on the signature description in terms of its local features and their relations. The comparison of features in the reference and tested signatures is conducted using Dynamic Time Warping technique.

1. INTRODUCTION

Handwritten signature is one of the popular biometric features that can be used in computer based authentication systems. Its widespread use and variety of applications encouraged researchers and commercial companies to investigate and develop algorithms for automatic signature verification. In over a decade of research many methods and complete systems found their applications in administration and finance institutions. However, there are no perfect solutions and the automatic signature verification is still an active research area. Due to the fact that handwritten signatures are highly susceptible to fraud and spoofing, it is very difficult to design the system that is both capable of recognition of genuine signatures from one side and resistant to forgery attempts from the other side. Forging a signature image is easy when a genuine example is available and it is very difficult to prove that such a forgery does not belong to the legitimate signature owner [1,10,16]. In order to improve forgery detection the dynamic information gathered during the process of signing is analyzed. Dynamic data such as time of writing, trajectory, pen velocity, acceleration and pressure are much harder to imitate. When taken into consideration, these parameters have significantly improved the correctness and hence success rate of signature recognition [2,4,6,9,15].

Most of the signature recognition systems make use of several genuine and forged signatures per subject during the training phrase, or select representative reference signature before building the database against which new signatures are tested. *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.

2. SYTEM STRUCTURE

Figure 1 illustrates the structure of the proposed signature verification system. The system operates in two modes: enrolment and verification. During the enrolment reference signature is captured and is stored as a reference pattern. In verification, the presented signature is verified for its authenticity by comparison against the reference pattern registered during enrolment.

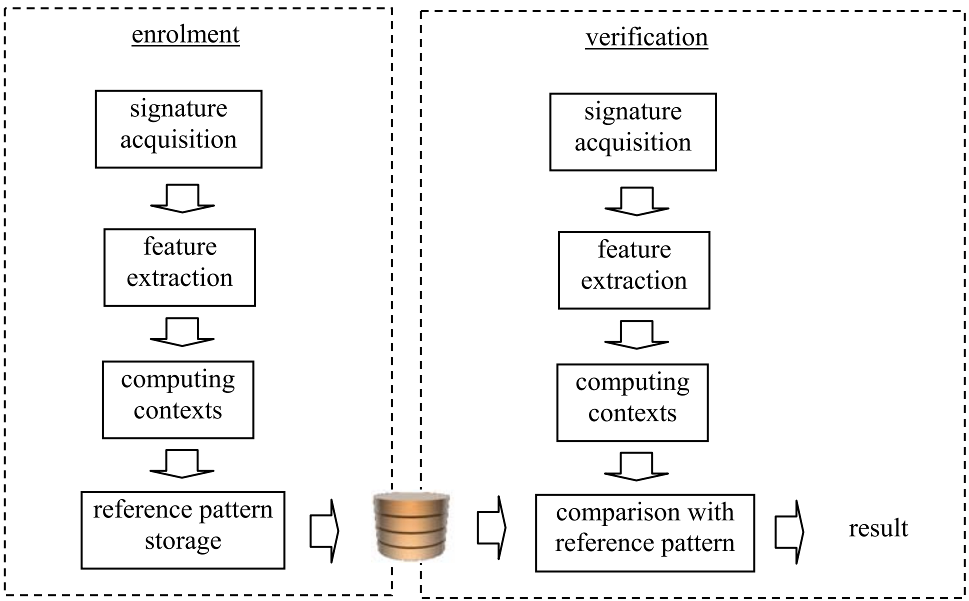

Fig.1 The system structure

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2.1. SIGNATURE ACQUISITION

The data acquisition stage is there where information about the questioned signature is collected. In order to register dynamic characteristics of the signing process a special input device is necessary. Dynamic data can be recorded by means of tablets, specialized signature pads or cameras where the trajectory of the signature is traced in video sequence.

2.2. FEATURE EXTRACTION

Basic dynamic data gathered at the time of signing can contain the following parameters: *X*, *Y* coordinates, pressure, elevation and altitude. The coordinates *X* and *Y* determine the position of the pen tip inside the controlled area where the signing process is being traced. The pressure parameter describes the pen pressure inflicted on the tablet surface. The altitude is the angle between the pen and the surface. The azimuth denotes the angle between the projection of the pen onto the writing surface and *X* coordinate axis.

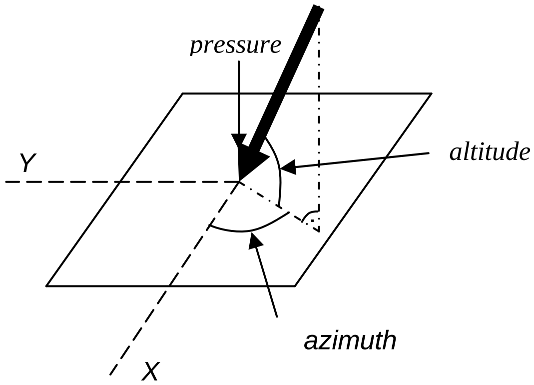

Fig.2 Signature parameters.

The following figure shows a signature sample and its parameters captured during signature registration.

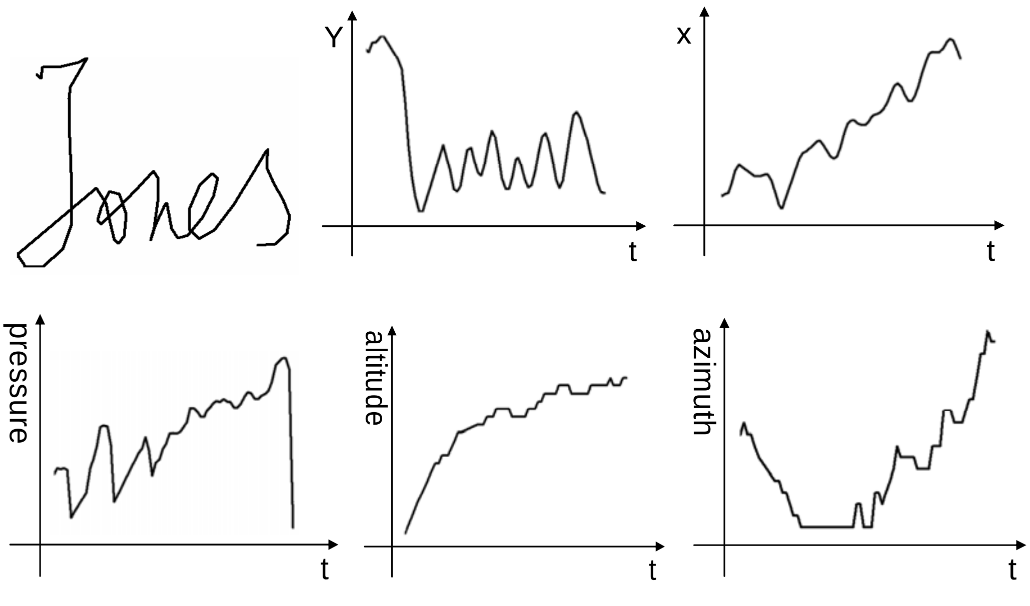

Fig.3 Sample signature and its dynamic parameters.

Each of those dynamic parameters can be recorded with time resolution up to 400 samples per second on the sampling time available in the acquisition device. According to studies on dynamics of handwriting the cut-off temporal frequency of signing process is below 20Hz. This fact allows for reducing the number of samples without losing information. Nyquist frequency requires in this case only 40 samples per second to retain all important components of writing parameters. The number of samples varies and depends on the signature writing time.

In the case of signature recognition, each signature object can be represented by the sequences of values denoting position, pressure, altitude and azimuth sampled during the signing process. From values of these sequences we can form vectors, each describing position, pressure, altitude and azimuth captured at a particular moment. The sequence of vectors describing the whole information gathered during signature registration can take the following form:

$$\text{Signature descriptor} = \left\{ \begin{bmatrix} x_1 \\ y_1 \\ p_1 \\ l_1 \\ z_1 \end{bmatrix}, \begin{bmatrix} x_2 \\ y_2 \\ p_2 \\ l_2 \\ z_2 \end{bmatrix}, \ldots, \begin{bmatrix} x_i \\ y_i \\ p_i \\ l_i \\ z_i \end{bmatrix}, \ldots, \begin{bmatrix} x_N \\ y_N \\ p_N \\ l_N \\ z_N \end{bmatrix} \right\} \tag{1}$$

where
x_i - X coordinate, y_i - Y coordinate, p_i - pressure, l_i - altitude, z_i - azimuth
$i = 1 \ldots N$ – sample number

2.3. COMPARISON WITH REFERENCE PATTERN

The length of the acquired feature vectors differs from one signature to another. Even in the case of the signatures given by a particular individual, each sample has different length and the parts of the signature have slightly different characteristics in time. In order to deal with these difficulties the resulted feature vectors are classified by means of Dynamic Time Warping algorithm [3,9]. This method allows for modelling the time-axis fluctuation with nonlinear warping function. The timing differences are eliminated by warping the characteristics of the signatures in such a way that the optimal alignment is achieved. DTW algorithm defines a measure between two sequences $x_1, x_2, \ldots, x_{N-1}, x_N$ and $y_1, y_2, \ldots, y_{M-1}, y_M$ as a recursive function:

$$D(i, j) = \min \left\{ \begin{matrix} D(i, j-1) \\ D(i-1, j) \\ D(i-1, j-1) \end{matrix} \right\} + d(x_i, y_j) \tag{2}$$

The distance $d(x_i, y_j)$ can be chosen in various ways depending on the application. In our case, the Manhattan distance is used. The calculations are carried out using dynamic programming. The key part of this algorithm lies in forming the so called cost matrix g. Its elements $g(i, j)$ are cumulative distances computed as the sum of distances $d(x_i, y_j)$ with one of the cumulative distances being found in earlier iterations (3):

$$g(i, j) = d(x_i, y_j) + \min\{ g(i-1, j), g(i, j-1), g(i-1, j-1)\} \tag{3}$$

The cost matrix enables to find a warping path that represents the best alignment and minimizes the overall distance given by the recursive function of Equation (2). In order to reduce excessive warping of sequences, a constraint is applied to restrict warping paths to a region called window.

2.4. COMPUTING CONTEXTS

During signature recognition the sequences of vectors representing reference patterns are compared with the vector describing the tested signature. The problem with this kind of comparison is that the values being matched have no information about the context in which they occur. This lack of contextual data may lead to incorrect results when features occurring in different contexts are treated as equivalent. Figure 4 illustrates this problem. Points, which occur in different contexts have the same value and will be recognized as equivalent during direct comparison.

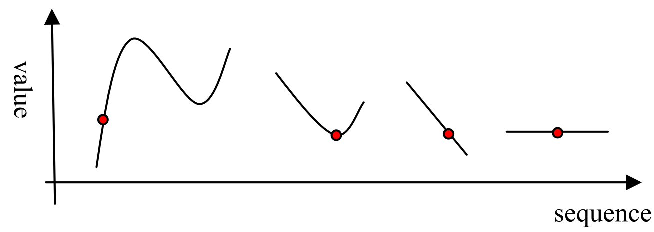

Fig.4 Feature points in different contexts

Context information has been successfully used in image recognition [8] and offline signature verification [14].

The contribution of this work is to introduce context information to dynamic features in online signature recognition. In works [8,14] context for each characteristic feature is computed using its relations to all other features describing particular object. In our work we constrain calculations of context information to local signature segments surrounding each feature value.

Different methods for context computation were used and tested experimentally. In the first method during feature comparison the distance measure between points is computed using averaging expression over neighbouring points in the sequence as given in Equation (4).

$$d_1(f_i, f_j) = \frac{\sum_{k=-C}^{C} d(f_{i+k}, f_{j+k})}{C} \tag{4}$$

The variables *f* and *f’* represent the values of parameters (such as coordinates or pressure) for the reference and tested signature respectively. Indexes *i* and *j* denote *i-th* value in the parameter sequence for the reference signature and *j-th* value for the tested signature. The size of the context *C* is selected experimentally and several trials were carried out for different values of this parameter.

In the second method weighting coefficient is introduced to Equation (4). The values of the weighting coefficients reduce the influence of the more distant points from the point of comparison in the sequence. The modified context is given in the Equation (5).

$$d_2(f_i, f_j) = \frac{\sum_{k=-C}^{C} w_k d(f_{i+k}, f_{j+k})}{\sum_{k=-C}^{C} w_k}, \quad w_k = \left|\frac{1}{k}\right| \tag{5}$$

In the third method the weighting coefficient was changed to the form given in Equation (6). The logarithm function used for calculation of w'_k also reduces the influence of the more distant points from the point of comparison but in a smaller amount than the previous method.

$$d_3(f_i, f_j) = \frac{\sum_{k=-C}^{C} w'_k\, d(f_{i+k}, f_{j+k})}{\sum_{k=-C}^{C} w'_k}, \quad w'_k = \frac{1}{1 + \ln|k|} \tag{6}$$

3. RESULTS

In order to evaluate the effectiveness of the system, several experiments were carried out. Online signature database from Signature Verification Competition [16] was used for all of the tests. For the signature verification the value of distance measure between the reference and tested samples is compared with a threshold level. If the value of the distance measure is below the selected threshold, the signature is considered as original, otherwise is recognized as a fake and is rejected.

The verification process can result in two types of errors. The first type of error is when the system fails to recognize the original signature and rejects it as a forgery attempt. This type of error is called False Negative usually described by False Rejection Rate (FRR). The FRR is defined as the percentage of identification attempts in which false rejection occurs.

The second type of error arises in False Positive when the system incorrectly accepts forged signature as a genuine one. This kind of error is measured using False Acceptance Rate (FAR). FAR is calculated as the ratio of the number of false acceptances divided by the number of total identification attempts.

The values of FAR and FFR depend on the threshold level. Decreasing the threshold results in lower number of false acceptances but also increases the allowed number of incorrectly rejected signatures. Increasing the threshold has an opposite effect as it lowers FRR but increases FAR error. Another way for describing the quality of the verification process in biometric systems is Equal Error Rate (EER). The value of EER is computed as the value of FAR and FRR when both of them have the same value, FAR=EER.

During experiments the signature test set contained both genuine and forged signature samples.. The forgery of the signatures was carried out by individuals who had access to the images of the genuine samples and had enough time to train how to imitate them. This kind of forgeries is often referred to as skilled forgery attempts. Three genuine signatures for 40 individuals were selected at random from the database and then for every person, each of the signatures was used as a reference pattern

The result achieved when using with direct comparison of values was of 3.6% EER. All available parameters (coordinates, pressure, altitude and azimuth) were used for signature verification.

Tables 2 show the results achieved by using context methods 1, 2 and 3. All experiments were conducted for different values of *C*.

Table 2. Signature verification results – the context method

C	*EER [%]*		
	method 1	*method 2*	*method 3*
3	4.2	4.3	4.3
5	3.1	3.7	3.6
9	3.3	3.3	2.9

As shown in Table 2 the introduction of context information into signature features description can improve the verification results. The selection of context measure and the size of the context are important. In our experiments best results were achieved for averaging expression with weighting coefficient based on the logarithm function (method 3) with the context size C=9.

4. CONCLUSIONS

In this work we proposed a dynamic signature verification system enhanced with feature context comparison. The achieved results show that when enhancement is considered to include context information as a replacement to the direct feature values, the verification rate can be improved. Three basic methods for context calculation were presented. Our current research concerns investigation of other methods for context information description and selection of the most appropriate context computation method for each kind of parameter separately. Inclusion of the context information needs additional computation and hence increases the system response time. The amount of additional time required in relation to direct comparison of features depends on the size of the context and method for calculation of the distance between contexts descriptions. In order to reduce the time required for context comparison we are also working on reducing the dimensionality of context data.

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