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Discriminative feature selection for on-line signature verification

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ABSTRACT

On-line handwritten signatures are collected as real-time dynamical signals which are written on collective devices by users. Since individuals have different writing habits, consistent and discriminative features should be selected to distinguish genuine signatures from forged signatures. In this paper, two methods, which are based on full factorial experiment design and optimal orthogonal experiment design, are proposed for selecting discriminative features among candidates. To improve the robustness, consistency of feature is analyzed at first, and more consistent features are selected as candidates for discriminative feature selection. To reduce the influences of fluctuations caused by internal and external writing environments changes before verification, signatures are effectively aligned to their reference templates based on Gaussian mixture model. A modified dynamic time warping with signature curve constraint is presented for verification to improve the efficiency. Comprehensive experiments are implemented based on the data of the open access databases MCYT and SVC2004 Task2. Experimental results verify the effectiveness and robustness of our proposed methods.

1. Introduction

As the requirements of information security and identity verification keep increasing, biometrics is gaining popularity as a more trustable alternative to password based security systems. On-line handwritten signature verification is one of the most acceptable technologies of biometrics due to the fact that handwritten signatures have long been established as the most widespread means of personal verification. On-line signatures are difficult to be imitated and forged because they are unique and consistent for a given period. Experimental results have indicated that the accuracy of on-line signature verification is not lower than other biometrics [1,2].

On-line signature verification could generally be divided into two groups, i.e., parametric approaches and functional approaches. In parametric approaches, signatures are represented by series of parameters or vectors. Several common parameters are used the most extensively, such as position, displacement, numbers of pen ups and pen downs, speed, acceleration, pen down time ratio, aspect ratio, etc. [3,4]. When functional approaches are concerned, signatures are usually characterized in terms of time functions, some of the most commonly used functions are position trajectory, velocity, acceleration, centripetal acceleration, pressure, direction of pen movement, azimuth angle and altitude angle, etc. [5,6]. Generally, the functional approaches would obtain higher accuracy and reliability because they contain more dynamic information [2,4,6]. But functional approaches often require heavy computation during the process of matching or dissimilarity evaluation and it is less efficient in most cases.

In verification, the authenticity of test signature is evaluated by matching its features with those stored in knowledge base for a given user. There are some commonly used verification methods, such as template matching methods [7,8], statistics based methods [9,10] and structure based methods [11,12].

2. Related works

On-line handwritten signatures are collected as real-time signals and presented as time series. By reasons of internal and external environment changes, there are fluctuations of size, location and rotation angle of signatures within the same user at different inputs. Moreover, signatures will not keep higher consistency for a long time since the writing habits and external environments change. In this study, it is necessary to reduce the influence of fluctuations caused by variances of size, location and rotation angle, which could worsen the performance of verification. Thus, it is very important to effectively align the test signatures to references before verification. Furthermore, consistent and discriminative features should be extracted and selected for reducing the influences of these fluctuations and distinguishing genuine signatures from skilled forgery signatures.

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Methods of signature alignment include size, location and rotation angle matching. In most of research works, signatures are aligned by size, location and rotation angle, respectively. In methods of size alignment, max-min normalization and z-score normalization [13,14] are the most used. Methods of location and rotation angle alignment are mainly mapping the location and rotation angle of test signatures onto the reference coordinate system. The location alignment commonly uses the initial point and signature centroid as reference point [15,16], while the rotation angle are aligned by minimum moment of inertia to reference system [17,18]. Recently, alignment methods based on Gaussian mixture model (GMM) are developed [19–22]. In these methods, one point set is treated as the GMM centroid with equal isotropic covariance, the alignment of two point sets is altered to the centroid of GMM matching by the maximum likelihood estimation, and the optimal solution can be obtained by the expectation maximization (EM) algorithm.

Effective and discriminative feature extraction and selection are important for the performance of on-line signature verification. Consistent and discriminative features are analyzed and selected for on-line signature verification in [2,6,11,15,23,24]. Different methods and criterions are presented in relevant works. Different conclusions are concluded based on different criterions. Most of these methods are mainly based on consistencies which mainly analyze the inter-similarities for a given user. To achieve higher accuracy for on-line signature verification, more distinctive and discriminative features should be extracted and selected to distinguish the genuine signatures from forgeries. In recent studies, feature's capabilities in distinguish between genuine and forged signatures are analyzed directly by using equal error rate (EER) values [25,26].

When template matching approaches are considered, dynamic time warping (DTW) is widely used [7,8,27]. DTW is a nonlinear optimization matching method. During the process of DTW matching, it allows the time axes being compressed or expanded of two signatures to obtain the minimum distance. However, heavy computation is one of the defects of DTW when sampled points included in signatures increases, which will decrease efficiency of on-line signature verification. Some researchers proposed modified methods to improve the efficiency of DTW [8,27–30]. Most of these works mainly emphasize on the data reduction, and some information of signature might be discarded during the verification.

2.1. Framework and motivations of the work

This work emphasize on reducing the inconsistencies of signatures and improving the effectiveness. Discriminative features are selected for improving the accuracy of verification. Our proposed method consists of several components, i.e., preprocessing, feature extraction and selection, verification, as shown in Fig. 1.

For a given user, the input signatures are collected by collective devices and are presented as dynamic time series. There might be noises, distortion and variation during signature acquisition caused by collective devices and writing habits. Moreover, by reasons of internal and external environments changes, there are fluctuations of size, location and rotation angle of signatures within the same user at different inputs. In preprocessing stage, signatures are preprocessed, including smoothing and alignment, to decrease the fluctuations which are caused by noises, distortion and variation of signatures.

In the feature extraction and selection stage, original features are extracted empirically at first. For improving the accuracy and robustness, consistent and discriminative features should be selected to distinguish genuine signatures from skilled forgery signatures. Thus, there are two steps included in the selection stage. (1) Step 1: consistent features are selected from original features to improve the robustness of the system; (2) Step 2: for improving the accuracy, discriminative features are selected among the consistent features. EER values are used as the performance indicator to evaluate the distinguishing quality for the features. Two methods of experiment designs are used respectively for discriminative features selection, i.e., factorial experiment design (FED) and orthogonal experiment design (OED), respectively.

After feature extraction and selection, more consistent and discriminative features are selected for verification. For improving the efficiency of the system, an efficient method of signature matching based on DTW with SCC (signature curve constraint) is proposed for signature dissimilarity evaluation. Then, authenticity of test signatures can be judged accordingly.

Contributions of our work can be mainly described from the following three facts.

- In order to reduce the interrupted noises and distortion, input signatures are fitted by cubic smoothing algorithm with five-point approximation. Signatures are aligned to their reference template based on Gaussian mixture model (GMM) to decrease influences caused by fluctuations of various size, location and rotation at different inputs.
- For improving robustness, more consistent features are selected as candidates for discriminative features selection. Then, discriminative features are selected among these consistent features by two methods of experiment design, respectively, i.e., full factorial experiment design (FED) and optimal orthogonal experiment design (OED). EER values are used directly to evaluate feature discriminative ability. Thus, features used in verification can be not only consistent within intra-class, but discriminative for inter-class to distinguish forgery signatures from genuine ones.
- For improving the efficiency, a modified dynamic time warping with signature curve constraint (DTW with SCC) is proposed. In DTW with SCC, features are not matched by DTW directly. Instead, features are matched with the location constraints, which are inherent in two matching signature curves. The dissimilarity of features between the test and reference signature is evaluated by DTW with SCC.

3. Preprocessing

Prior to signature verification, the user should be familiar with the signature acquisition device and should be required to input signature skillfully. On-line signature is then captured and represented as dynamic time series through acquisition devices at fixed interval. There might be noises, distortion and fluctuations during the acquisition. To decrease influences caused by these noises and fluctuations, signatures should be preprocessed before verification.

3.1. Smoothing

At first, signatures should be smoothed to reduce the interrupted noises and distortion. Set the signature curve as$s(n) = \{(x(n), y(n)), n = 1, 2, \cdots, N\}$, each points included in signature can be fitted by cubic smoothing algorithm with five-point approximation, and the parameters can be estimated by the least square algorithm. Middle points of signature can be approximated

$$s'(n_1) = (-3s(n_1-2) + 12s(n_1-1) + 17s(n_1) + 12s(n_1+1) - 3s(n_1+2))/35 \tag{1}$$

where, $n_1 = 3, 4, \cdots, N-2$.

The first two points of signature can be approximated by

$$s'(1) = (69s(1) + 4s(2) - 6s(3) + 4s(4) - s(5))/70 \tag{2}$$

$$s'(2) = (2s(1) + 27s(2) + 12s(3) - 8s(4) + 2s(5))/35 \tag{3}$$