Template Selection for On-line Signature Verification

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Abstract

In this paper, we propose two effective methods to perform automatic template selection where the goal is to select prototype signature templates for a user from a given set of online signatures. The first method employs a clustering strategy to choose a template set that best represents the intra-class variations, while the second method selects templates that exhibit maximum similarity with the rest of the signatures.

In the experiment, two typical online signature verification have been employed, respectively based on global and local features, and the verifying results on a database Task2 of SVC2004 (First Signature Verification Competition 2004), with 20 genuine signatures and 20 skilled forgeries for each set, indicate that two proposed selection procedures as presented here results in better performance than random template selection.

1. Introduction

Automatic signature verification has been an intense research area because of the social and legal acceptance, and widespread use of written signatures such as access control, security, or financial and contractual matters [1, 2].

The signature verification generally is divided into two vast areas: off-line methods that assume no time-relayed information, and on-line ones with time-related information available in the form of multi-dimensional function of time.

For on-line signature verification, it is obvious that the stability of the signatures associated with an individual is of influence on the verification accuracy. However, the signature data acquired from an individual is susceptible to changes due to variations in environmental factors (unaccustomed place, posture of the writer, type of pen and tablet, size of the writing area, etc.) and alteration in the signature trait itself (the development of handwriting habit, the difference in emotion of the signer, etc.). In a word, the signature measurements tend to have a large intra-class variation, thereby it is possible to select the significantly different prototype signature and store them as templates for verification, and this paper focuses on template selection for online signature verification.

Limited literature and methods have been proposed to deal with the problem of automatic templates selection for online signature verification system [3, 4]. Based on correlation-based criterion, a measure using DMP (direct matching points) to select the near-optimal set of reference signatures is proposed in [3], and the paper [4] presents a method that establish personalized templates for automatic signature verification based on analysis of both shape of the signature and the dynamic of the writing process. Both methods obtained a good performance for online signature verification by selecting a optimal templates set, however, there are still issues, such as complexity in implement and time-consumption, for example, the method proposed in [4] cost less than 1 minute for construct the template of a person.

This paper proposes two simple and effective templates selection methods for online signature verification that attempt to represent the variability as well as typicality in a user's signatures date. Our experiment in section 3 validates the effectiveness of the proposed methods in two typical online verification approaches: the one based on global features and the other based on local features, and the signature verification proceeds in two distinct stages: the enrollment stage and the authentication stage, as illustrated by Figure 1.

This paper is organized as follow: Section 2 describes the two methods of template selection for on-line signature verification. Section 3 introduced two signature verification approaches based on global features and local features respectively. Section 4 provides experimental procedure and results. Section 5 draws the conclusions of this work.

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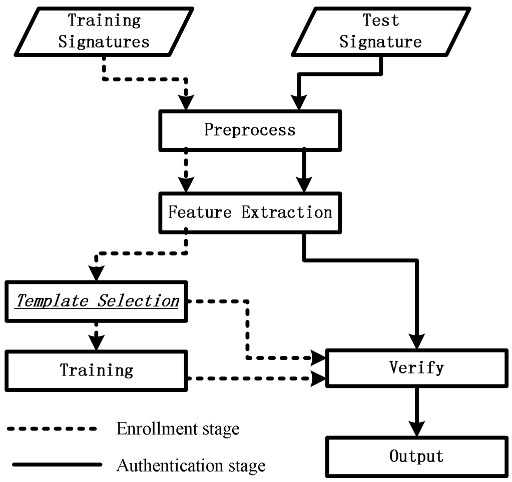

Figure 1. Procedure of signature verification system

2. Template selection for signature verification

The problem of templates selection for signature verification can be described as follows: given a set of N signatures corresponding to a user, select K templates that 'best' represent the variability as well as the typicality observed in the N signatures, K<N, and the value of K is predetermined.

To solve this problem, we propose two methods: Method 1 based on cluster tree and Method 2 using minimum average distance criteria.

Method 1: Specifically, Hierarchical clustering is a way to investigate data grouping simultaneously over a variety of scales, by creating a cluster tree. The tree is not a single set of clusters, but rather a multilevel hierarchy, where each terminal node corresponds to a signature and the intermediate nodes indicate the formation of clusters (see Figure 2).

The template set T, |T| = K, is selected as follows:

1. Calculate the N×N dissimilarity matrix M, where entry M (i , j), i, j ∈{1, 2… N} is the distance score between impressions i and j.
2. Apply link clustering algorithm on M to generate the cluster tree D.
3. Do for k = 1, …, K templates:
   - Select a signature whose average distance from the rest of the signature in the cluster is minimum;
   - If a cluster has only two signatures, choose any one at random;
4. Constitute the template set T.

Method 2: The second method simply sorts the signatures based on their average distance score with other signatures, and then selects those signatures that correspond to the K smallest average distance scores as templates set. For each user:

1. Do for j = 1, …, N signatures:
   - Calculate the distance scores of j th signatures respect to the other (N−1) signatures;
   - Compute its average distance score d_j;
2. Choose K signatures that have the smallest average distance scores;
3. Constitute the template set T.

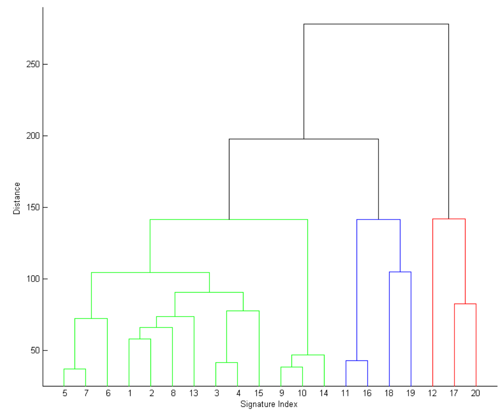

Figure 2. Binary cluster tree generated by dissimilarity matrix M

The proposed methods involve calculating the distance of two signatures. Specifically in the following section 3, we use the Euclidean distance on the global features and adopt a modified dynamic time warping algorithm to calculate the distance between two signatures on local features respectively.

3. Two signature verification approaches

In this section, two typical approaches for on-line signature verification are introduced. According to the utilization of on-line signature data, they can be divided into: i) approach based on global features. The feature vector consists of a set of global features ii) approach based on local features, in which the features are described by time sequences of the signature local properties.

3.1 Preprocessing

In the preprocessing stage, A commonly method is used to smooth the signature based on a Gaussian filter.

Both implemented systems do not resample signatures in preprocess stage, because resampling results in significant loss of information and critical points of the signature [5].

3.2 Signature verification based on global features

In this section, global features are introduced, and then a signature verification algorithm using majority classifier is presented.

The complete set of global features is given in Table 1.

Type	Feature Description
Spatial Feature	*1. Signature Width*
	2. Signature Height
Dynamic Feature	*3. Max pressure*
	4. Average pressure
	5. Time cost
	6. Average velocity x
	7. Average velocity y
	8. Positive mean velocity x
	9. Positive mean velocity y
	10. Negative mean velocity y
	11. Negative mean velocity y
	12 Max velocity x
	13 Max velocity y

Table 1. Two kinds of global features: i) the spatial features are usually useful for detecting random forgery. ii) the dynamic features, have good discriminative power beyond shape features, because they are hard to be imitated by observing the signature shape only.

Based on proposed global features, Majority classifier is now employed. Defined by equation (1):

$$\mathrm{N} = \left| \left\{ i : \frac{|f_i - \mu_i|}{\sigma_i} \le \lambda \right\} \right| \qquad (1)$$

The majority decision rule is f_i is declared a genuine signature if $\mathrm{N} \ge n/2$ and a forgery if $\mathrm{N} < n/2$.

Therein f_i be the value of feature i for the candidate signature being tested; μ_i and σ_i represent the sample average and sample standard deviation of feature i; n denotes the total number of features used in decision process and here is equal to 13; let λ be a fixed threshold.

3.3 Signature verification based on local features

In this section, local features are presented firstly, and then a modified dynamic time warping algorithm is exploited to align different-length signatures to calculate their distance, a signature verification system using LDA (linear discriminate analysis) classifier is employed.

Only two features are extracted at each sample point, which correspond to the position change in x direction and y direction respectively [$\Delta x, \Delta y$], and those features give the lowest error rate and are also invariant with respect to translation [5].

In order to calculating the overall distance between two different-length signatures R (Reference) and T (Test) in nonlinear time, DTW (dynamic time warping) algorithm is employed, as in equation (2):

$$D(i,j) = \min \begin{cases} D(i-1,j) & + d(i,j) \\ D(i-1,j-1) & + d(i,j) \\ D(i,j-1) & + d(i,j) \end{cases} \qquad (2)$$

where $d(i,j)$ denotes the distance between i *th* point of testing sample T and j *th* point of Reference R in the warping-path.

The final distance between two strings uses an additional global measurement: a sample points count difference penalty term.

$$Dist(T,R) = D(T,R) + \eta * |N_r - N_t| \qquad (3)$$

where $Dist(T,R)$ denotes the total matching distance between reference signatures R and testing signature T, η is the penalty, and $N_t (N_r)$ is the number of sample points $T(R)$.

In order to use training sets as many as possible, we introduced user-dependent feature normalization procedure to train the system described by Kholmatov et al. [5], which received the first place at SVC2004 with a 2.8% error rate.

A linear classifier with criterion of the minimum wrong sub-samples conjunction with the principal component analysis (PCA) has been trained to perform signature verification based on the normalized features. Using PCA, the dimensionality is reduced from three to one while keeping most of the variance, as the three features are highly correlated.

4. Experimental results

In our experiment, a public database of SVC2004 Task 2 is employed [2]. The corpus consists of 1600 signatures from 40 people (20 genuine signatures and 20 skilled forgery each subject).

In order to validate the effectiveness of the proposed methods for the automatic signature verification, both methods have been used to select 10 templates signatures among the 20 reference signatures available for each writer to construct the training set (400 signatures totally), and signatures not involved in training process are used for system performance evaluation (400 genuine signatures and 800 skilled ones totally).

The Performance described by ROC curves is shown by Fig. 2 both for approach based on global features (continue line) and approach based on local features (dashed line). and three sets of experiments are conducted based on: i) random template selection; ii) templates selection by Method 1; iii) templates selection by Method 2.

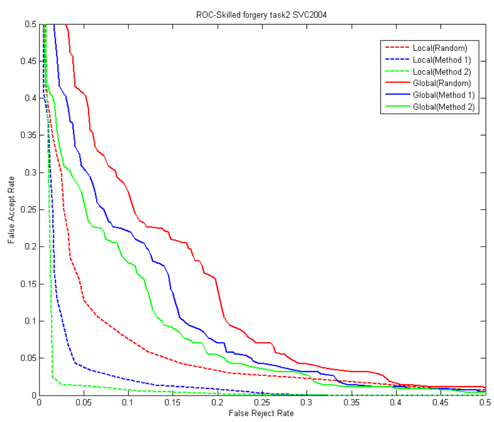

Figure 3. Performance of two approaches using proposed method 1 (blue lines) and method 2 (green ones) compared to random selection (red ones) for template selection.

From Figure 3, we can see that local approach using Method 2 for template selection has received the best performance with EER 2.84%. Moreover it also shows that local approaches have achieved a better performance compared to global ones, because the discriminability power of local features are better than global features for on-line signature verification.

From Table 1, it can be found that the percentage of randomly selected template sets that have a lower EER than the template sets selected by the proposed methods are about 4% and 6% for Method 1 and Method 2 respectively, therefore we suggest that automatic template selection is prior to random selection.

Compared to Method 1, Method 2 has received a better result in performance, and the reason could be that the templates set selected by Method 2 exhibit maximum similarity with other signatures, and Method 1 has a tendency to select the outliers thereby increasing the probability of false rejects.

Compared to the methods proposed in [3, 4], the proposed methods are more simple and effective, because the proposed methods need no other special technique to extract features for template selection, just as same as the features using to verify at the authentication stage.

	Random	*Method 1*	*Method 2*
Global	18.04%	14.68%	12.50%
Local	8.83%	4.12%	2.84%

Table 2. Performance measured by EER

5 Conclusion

In this paper, two simple and effective approaches to perform template selection for online signature verification are proposed. Two typical signature verification based on local and global features are respectively introduced to validate the proposed methods, and in our experiments, we demonstrate that automatic selection of templates is expected to result in a better performance of an automatic online signature verification system compared to a random selection, it is also observed that proposed Method 2 technique results in better performance than Method 1.

Acknowledgments

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