Off-Line Signature Verification Based on Local Structural Pattern Distribution Features

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Abstract. Handwritten signature is a widely used biometric. The most challenging problem in automatic signature verification is to detect skilled forgery which is similar to the genuine signatures. This paper presents a novel method for extracting features for off-line signature verification. These features is based on probability distribution function, which characterizes the frequent structural patterns distribution of a signature image. Experiments were conducted on an publicly available signature database MCYT corpus. Experimental results show that the proposed method was able to improve the verification accuracy.

Keywords: Off-line signature verification, Pattern recognition, Local structural pattern, Chi-square distance.

1 Introduction

With the increasing security requirements of todays society, biometrics is playing a more and more important role. As one of the oldest biometrics, signature is the result of rapid human movements depending on the psychophysical state of the signer and the signing conditions. The signature verification system performs one-to-one and determines whether the two samples of handwriting were written by the same person.[17] Approaches to signature verification fall into two categories: on-line and off-line [14]. Even today, high success rates are still limited to the on-line.[1] This is because on-line signature verification can capture dynamic features like time, pressure, speed and the order of stroke. However, off-line verification is more user friendly and have a significant advantage in many of the practical uses since they do not require access to special device. Up to now, off-line signature verification still an open research area needed more efforts to address it. In signature verification system, three kinds of forgery may be considered: random forgery, simple forgery, and skilled forgery[4]. Naturally the skilled forgery is very similar to the genuine signatures and is more difficult to be distinguished, especially for off-line signature verification due to the lack of dynamic information, so skilled forgery detection is the most challenging job for off-line signature verification[10].

During the last few years, researchers have tried different methods with various approaches to detect the skilled forgeries detection. An extensive overview of previous work is included in [14,3]. J. F. Vargas et al. [7] proposed an off-line signature verification system based on grey level information using texture

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features. They adopted the co-occurrence matrix and local binary pattern as features. In [13], surroundedness feature is proposed, which contains both shape and texture property of a signature. K.Tselios et al.[9] proposed grid-based feature distributions, this method explored the relative pixel distribution along a signature trace.

In this paper, we mainly present new and very effective techniques for signature verification that use probability distribution functions extracted from the scanned images of handwriting to characterize signer individuality. This paper is organized as follows: Section 2 presents the preprocessing and the feature extraction methodology. Section 3 shows the experimental results based on MCYT corpus. Finally ,conclusions are discussed in section 4 .

2 Methodology

In order to perform verification of a signature, several steps must be performed. Figure 1 illustrates the whole signature verification process.Initially the scanned signature image is preprocessed. The out image is used to extract features.Finally signature is verified by matching extracted features against those stored in the database.

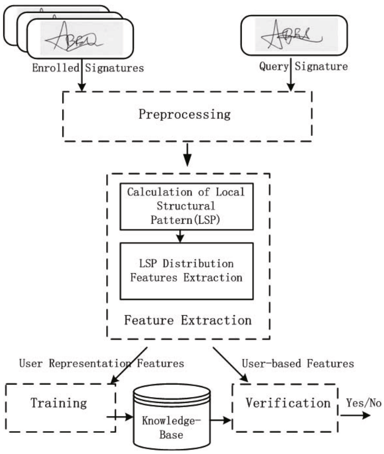

Fig. 1. Block diagram of the proposed verification system

2.1 Preprocessing

Some preprocessing steps have to be applied to the input signature images. the signature images are first binarized using the OSTU algorithm [11]. And then, we apply mathematical morphology method is used to remove the noise of small area. Finally, edge detection based on Sobel operator was performed on each signature image. Figure 2 shows an example of processed signature image.

(a) Original signature (b) The binarized signautre after remove noise (c) Extracted edge map

Fig. 2. Sample of original and after-preprocessing signature

2.2 Feature Extraction

Similar to many other pattern recognition problems, feature extraction is a crucial step. In off-line signature verification , an efficient feature extraction technique should adequately describe the information of signature and could be tolerant to intra-user variability. Additionally, in order to detect skilled signature where forgeries are visually much similar to the genuine signatures on a global scale, local measurement to extract pertinent detailed information are needed. In this paper, we use local structural features to uniquely characterize a candidate signature, and these features characterizes the frequent structural pattern distribution, and the steps are as follows:

The first step of generating the new feature is extracting segments block of signature. To obtain these patterns, we use a $n \times n$ sliding window that is slid over an edge-detected binary handwriting image, and for each sliding window, the central pixel is on the edge pixel. The size n of window is even, and should be large enough to contain ample information about the style of the writer and small enough to ensure a good identification performance[15].Regarding the mask size n, we carry out an exhaustive study with sizes of 7×7,9×9,11×11,13×13 for our system. The effect of mask size on verification performance has been analyzed in detail in Section 3. The method has been illustrated in figure 3.

For simplify, we employ a part of signature as sample in figure 3. In the sliding window, the numbers 1 and 0 represent edge pixels and non-edge pixels respectively, and the red pixel represents the center edge pixel. each window is a segments block of signature, and the number of the segments block is equal to the number of the edge pixels for a signature image.

After obtaining the segments block, we need model each segments block through encoding. each segments block mainly provides of two-part information including shape information of the main segment and structural information of different segments, as shown in figure 4, different numbers represent the different connected domains. Every segment is a connected domain in sliding window, and the main segment is including the center pixel. we could describe the whole signature through coding the main segments. In addition, there is more than one connected domain in each sliding window, and structural information between different connected domains also need to be described. So, we model local patterns from two aspects including the main segment and the different segments. For the main segment in the sliding window, all pixels except for the central pixel could be divided into multiple groups according to the different Chebyshev-distance [2] between the central pixel and other pixels. All pixels

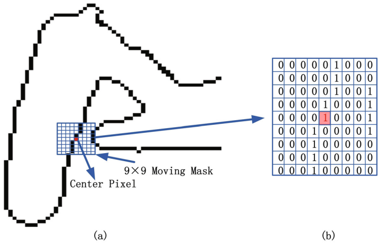

Fig. 3. Extracting segments block of signature(a)Sample of edge-detected binary signature image with a sliding window,(b)A segments block

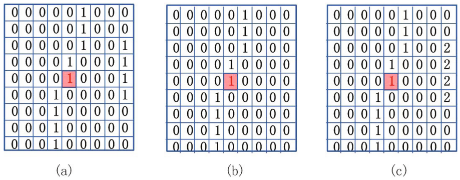

Fig. 4. (a)A local structural pattern,(b)The main segment,(c)multiple segments

with distance r form a binary sequence in accordance with a certain order such as counter-clockwise, and each binary sequence finally produces a decimal value lm. That is to say, each lm is a pattern which denotes the shape information of the main segment and we use LSPM to stand for these patterns. Additionally, it is worth noting that we only focus on pixel set containing at least two 1 to reduce the impact of noise. For example, it can be seen from 5 that around he center pixel, the size of sliding window is 7, the decimal value at distance 1 is 36, at distance 2 is 4112,at distance 3 is 262208,and at distance 4 is 16777472.

For multiple segments, we use the similar way to code. But, we only consider pixel sequences including different connect domains in order to represent the structural relation between different segments. As shown in figure6, for distance $r = 1, 2, 3$, these pixels from the same connected domain, so these pixel sequences are ignored and only the pixel sequence with distance 4 are encoded. For simplicity, the experiments below use a coding scheme that splits each pixel sequence into multiple binary sequence, and each binary sequence contain only two number 1 which are from two different connected domains.Thus, each pixel sequence maybe produce multiple decimal values ls. As illustrated in figure6. Here,we use LSPS to represent the structural information between the different segments.

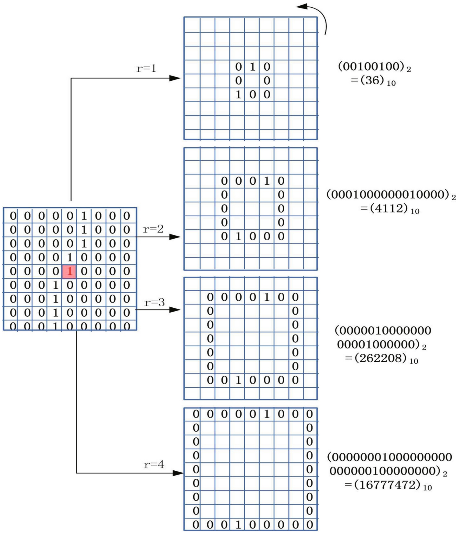

Fig. 5. Code for the main segment

Through above steps , all local structural patterns(LSPs) which consist of LSPM and LSPS are obtained. The third step is creating LSP distributions (LSPD). Therefore, in this step, we calculate frequency of each LSPM and LSPS respectively, which is given by:

$$H1_r(lm) = \frac{LSPM_r(lm)}{\sum_{r=1}^{(n-1)/2} LSPM_r(lm)} \tag{1}$$

$$H2_r(ls) = \frac{LSPS_r(ls)}{\sum_{r=1}^{(n-1)/2} LSPS_r(ls)} \tag{2}$$

where r corresponds to distance between center pixel and around pixels in sliding window, and n is the size of sliding window.i.e., if 7×7 size window is used then n is $7.LSPM_r(lm)$ is the number of LSPM pattern lm at distance r.Similarly,$LSPS_r(ls)$ is the number of LSPS pattern ls at distance r.

Therefore, the LSPD is defined as

$$LSPD = \{H1_r(lm), H2_r(ls)\} \tag{3}$$

2.3 Classification

The above described features are extracted from a sample group of signature images of different person. In the classification phase, various classifiers have

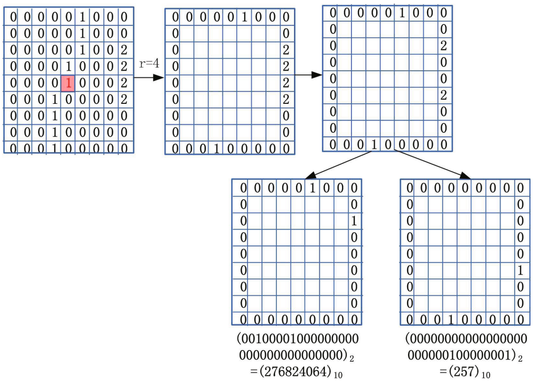

Fig. 6. Code for the different segments

been exploited to authenticate handwritten signatures. In this work, we use Chi square distance, which is one of well-known goodness-of-fit statistics[16], is adopted:

$$\chi^2 = \sum_{s=1}^{S} \sum_{l=1}^{L_s} \frac{(S_{sl} + M_{sl})^2}{(S_{sl} - M_{sl})} \tag{4}$$

where S is the number of scales and L_s is the number of LSP pattern types on scale s and S_{sl} and M_{sl} correspond to the sample and model probabilities at pattern l on scale s, respectively.

During verification, a claimed signature is compared against our template file using Chi square distance and if it is below a certain threshold value, then this signature is accepted as genuine, otherwise it is rejected to be a forgery. Here, we use localized thresholds.What this means is that each signature that is stored in the template will be stored with its own unique threshold.

3 Experiment and Results

Experiments are conducted on the publicly available signature database MCYT corpus. We adopt AER(Average Error Rate),FAR(False Acceptance Rate) and FRR(False rejection rate) to evaluate the verification performance.

3.1 Signature Database

MCYT is a bimodal databaseis used for the experiments. [12] Off-line signature subcorpus comprises 2250 signature images, with 15 genuine signatures and 15 forgeries per user (contributed by three different user-specific forgers). The 15 genuine signatures were acquired at different times (between three and five) of the same acquisition session. At each time, between 1 and 5 signatures were acquired consecutively.[6]

In the training and testing phase, the genuine (for threshold calculation) training samples will be chosen randomly from the database set and the test will be performed with the other genuine and forged samples. In order to obtain reliable results in each studied case, the training and test procedure was repeated 10 times with different randomly chosen training sets. In our experiment, 10 genuine samples were used for training, five genuine samples and 15 forgery samples were used for testing.

3.2 Experimental Results on Different Window Sizes

The selection of the sliding window size would directly affect verification performance.

Table 1. Experiment results with different window sizes on MCYT corpus

Window size	FAR(%)	FRR(%)	AER(%)
7×7	8.72	14.94	11.83
9×9	6.58	14.4	10.49
11×11	3.56	14.94	9.25
13×13	4.8	15.2	10

From Table 1 , we can find that error rate will change with the number of window size increases. This is because that if the sliding window size is too small, the description of local structural pattern is not comprehensive, because no two signatures by the same person are identical on a detailed scale, and error rate will be increased. On the contrary, if the sliding window size is too large, the set of features would contain much redundant information, and the error rate would also be increased.

3.3 Comparison with Some Other Published Methods

The lack of a standard international signature database, so a comparison of the performance of different signature verification systems is a difficult task. For the sake of completeness, we present some results obtained by published studies that used the MCYT corpus in Table 2.

Table 2. Performance comparison of the proposed methods with other published methods

Method	AER(%)
[5]	22.4
[8]	15.02
[7]	11.28
proposed method	9.25

4 Conclusion

In this work, a feature extraction technique for analysing the handwrittern signature for verification tasks is proposed. The method is based on the idea of statistically exploiting the relative local structural pattern distribution by the sliding window. Verification is based on Chi-square distance classification algorithm.Experimental results demonstrated that the proposed method achieved favorable verification performances.Further work is expected to be carried out towards the study of the selection of features and other handwrittern datasets.

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