Using SIFT Features in Palmprint Authentication

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Abstract

As a new branch of biometrics, palmprint authentication has attracted increasing amount of attention because palmprints are abundant of line features so that low resolution images can be used. In this paper, we present two novel approaches for palmprints authentication. Firstly, we employ the SIFT (Scale Invariant Feature Transformation) for palmprint authentication. Point-wise matching is used to match SIFT key points extracted form palmprint images. Secondly, we extend a time series technology, SAX (Symbolic Aggregate approximation), to 2D data for the palmprint representation and matching. Using a public palmprint database, we demonstrate that the two proposed approaches, when combined together, can achieve the palmprint authentication accuracy comparable to that of the state of the art algorithms.

1. Introduction

Recently, a novel hand-based biometric feature, palmprint, has attracted an increasing amount of attention. Palmprints are believed to have the critical properties of universality, uniqueness, permanence and collectability for personal authentication [1]. What's more, palmprints have some advantages over other hand-based biometric technologies, such as fingerprints and hand geometry. Palms are large in size and contain abundant features of different levels, such as creases, palm lines, texture, ridges, delta points and minutiae. Faking a palmprint is more difficult then faking a fingerprint because the palmprint texture is more complicated; and one seldom leaves his/her complete palmprint somewhere unintentionally. Also, compared to fingertips, palms are more robust to damage and dirt. What is more, low-resolution imaging can be employed in the palmprint recognition based on creases and palm lines, making it possible to perform real time image preprocessing and feature extraction. Among the four common hand-based biometric features: fingerprint [2], hand geometry [3], palm vein [4] and palmprint [1], the palmprint is believed to be able to achieve the authentication accuracy comparable to that of the fingerprint, and is higher than the accuracies of the hand geometry recognition.

Texture and palm lines are the most clearly observable palmprint features in low resolution images [5], and thus have attracted most research efforts. In the palm line based methods, the slope, intercept, inclination or orientation of palm lines are used as features [6][7]. In texture based approaches, texture features are extracted by filtering palmprint images using filters such as the Gabor filter [8][5], the ordinal filter [9], or the wavelet [10].

For the purpose of extending the palmprint authentication technology, we propose a novel representation and matching method for palmprint incorporating SIFT (Scale Invariant Feature Transformation) [11]. SIFT has already been widely used in generic object detection problems. Recently, its application in face authentication [12] and fingerprint verification [13] has also been studied.

The rest of this paper is organized as follows. Section 2 describes the preprocessing of palmprint images. Section 3 introduces SIFT extraction for palmprints. In Section 4, we present a palmprint feature representation using an extension of a time series technique, SAX (Symbolic Aggregate approximation). Palmprint authentication will be performed through score level fusion of the SIFT feature and the SAX feature. The corresponding experimental results will be reported in Section 5. The last section is a conclusion of our work.

2. Palmprint Image Preprocessing

The PolyU Palmprint Database Version II [14] will be used for all the experiments in this work. This Database contains 7752 grayscale palmprint images (384x284pixels, 96dpi) corresponding to 386 different palms. For each palm, there are around twenty samples collected in two sessions, where around ten samples were captured in both the first session and in the

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second session. The average interval between the first and the second sessions was two months. Before the feature extraction, the palmprints are aligned to a predefined universal coordinate for the extracting the ROIs. We adopt a palm coordinate system similar to the second square-based palm coordinate system proposed in [1]. The following steps are performed for

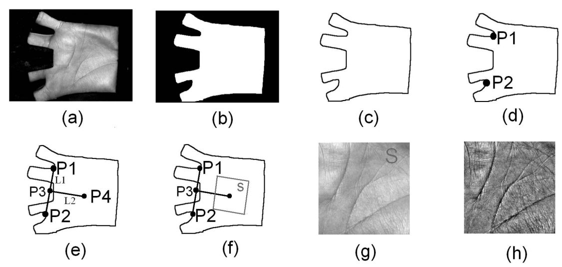

Figure 1. Palmprint image preprocessing

the palmprint alignment as is illustrated in Figure 1.

1) The palmprint image is binarized; isolated pixels, spurs and leaks are removed (Figure 1b).

2) The palm boundary is obtained using boundary tracking (Figure 1c).

3) The maximum curvature points P1 and P2 between the fingers are located using the curvature maxima finding (Figure 1d).

4) Connect P1 and P2 to get L1. Draw line L2 to pass through the middle point P3 of L1 perpendicularly. A point P4 is found on L2 so that the length between P3 and P4 equals a predefined value (Figure 1e).

5) A square area S of fixed size (135x135 pixels) is extracted with P4 as its center. S is defined the ROI for the succeeding feature extraction (Figure 1f/1g).

6) Non-uniform illumination correction is performed to enhance the palmprint texture (Figure 1h).

The extracted palmprint ROIs will be used for the feature extraction described in the following two sections.

3. SIFT on Palmprints

SIFT was proposed to detect local image features invariant to image scaling, translation, and rotation [11]. This is achieved by selecting key locations at local maxima and minima of a difference of Gaussian function applied in scale space, which is constructed by successively down sampling the input image. Maxima and minima of this scale space function are determined by comparing each pixel to its neighbors. More detail description of this process can be found in the original paper by Lowe [11]. Around each detected local maxima or minima, a 16x16 window is used to generate a histogram of gradient orientation. A SIFT feature key point consists of a local maxima or minima, together with the gradient histogram. During matching, all the SIFT key points of two images are compared. A SIFT key point is matched only when the distance between this point and its nearest neighbor is significantly larger than the distance between this point and its second nearest neighbor.

The preprocessed palmprint ROIs are used for SIFT feature extraction. Figure 2 shows several sample palmprint SIFT extraction results. Palmprint matching is achieved using the point-wise SIFT feature key point

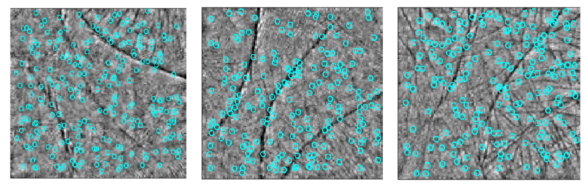

Figure 2. Sample palmprint SIFT features

matching process described above. The Euclidean distance is used as distance metric.

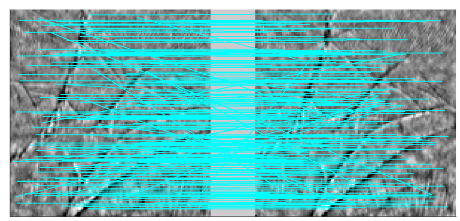

Figure 3. 245 point pairs are matched

Figure 3 shows the point wise matching result of two palmprints captured from the same palm. It can be observed that the point wise matching have generated some erroneous matched point pairs. A simple stratagem is employed to remove some of these false matching. As shown in Figure 1, the palmprint ROIs are aligned according to the palm shapes, indicating that the geometric variations appearing in the ROIs are limited to small rotations or translations. Therefore, we

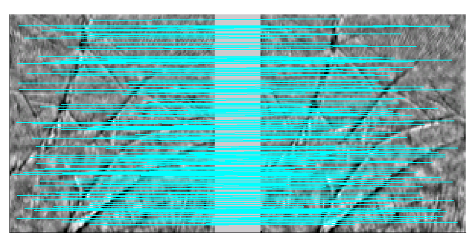

Figure 4. 228 point pairs are matched

remove the matched point pairs in which the spatial Euclidean distance between the two points are larger than a fixed threshold. Figure 4 shows the matching results after false matching removal.

As a general purpose feature, SIFT usually cannot achieve very high accuracy for a specific biometrics. This has been revealed in [12][13]. However, it can be used to improve the accuracy of other authentication methods through fusion. In the next section, we will introduce another palmprint authentication method.

4. Palmprint Authentication using 2D SAX

A time series technology, SAX, has been used for palmprint authentication in [15]. The basic idea of this approach is to convert 2D palmprint images into 1D time series for the SAX symbol string extraction and matching. However, the loss of the 2D neighboring information during the time series conversion has greatly limited the authentication accuracy of this approach. To facilitate a more effective SAX conversion for 2D data, we propose the 2D SAX, an extension of the SAX, which represents a real valued 2D data as a 2D matrix of symbols.

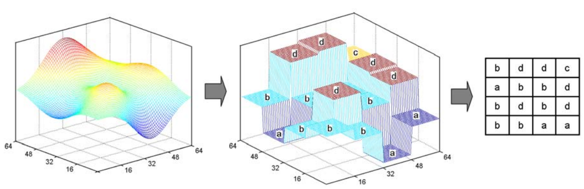

Figure 5. Conversion of a data into 2D SAX

Assume that the size of the input data Q is $m\times n$. First, Q is normalized to have a zero mean and a unit standard deviation. Then, similar to the PAA (Piecewise Aggregate Approximation) representation, Q can be represented by a matrix Q^* of the size $w_1\times w_2$. The (i_{th}, j_{th}) element of Q^* can be calculated by Equation (1). Simply stated, the original data Q is divided into $w_1\times w_2$ equal area blocks, and the mean value of the data falling within each block is calculated to form the dimensionality reduced representation Q^*. Finally, breakpoints identical to those used in 1D SAX conversion are applied to convert Q^* into a symbol matrix Q^, or the 2D SAX representation. The definition and property of these breakpoints can be found in [16].

$$Q^*(i,j)=\frac{1}{w_1 w_2}\sum_{x=\frac{m}{w_1}(i-1)+1}^{\frac{m}{w_1}i}\;\sum_{y=\frac{n}{w_2}(j-1)+1}^{\frac{n}{w_2}j} Q(x,y) \qquad (1)$$

Figure 5 illustrates the process of the 2D SAX conversion. In particular, the 2D *SAX_Length* is now defined as $w_1\times w_2$; and the definition of the 2D *SAX_Level* is identical to that in the 1D case. The similarity measurement *MINDIST* for 2D SAX is defined analogous to its definition for the 1D case [15].

The palmprint ROIs extracted in Section 2 are

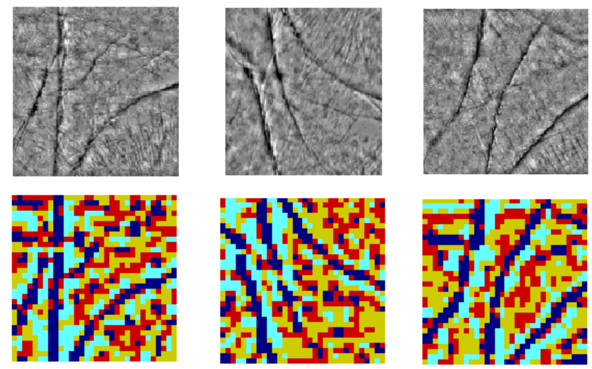

Figure 6. Sample palmprint 2D SAX

firstly filtered using an average filter for suppressing noises caused by factors such as dirt and damage. Then the filtering outputs are converted to 2D SAX representations. Figure 6 shows several palmprint ROIs and their corresponding 2D SAX representations.

For two palmprints, the *MINDIST* between their 2D SAX representations is used as the matching score. The smaller the *MINDIST* is, the more similar the two palmprints are. As human palm is a particularly flexible organ, distortions are unavoidable during palmprint capturing, leading to the fact that no alignment scheme will be able to extract the ROI perfectly [1]. We need to vertically and horizontally translate one of the templates to find the best matching, or the smallest *MINDIST* value.

5. Experimental Results

Three sets of complete one to one matching experiments were performed on the PolyU palmprint database. For each set of experiments, there are altogether 74068 genuine matchings and 29968808 imposter matchings. In the first set of experiment, only the SIFT feature is used for palmprint matching, and in the second experiment, only the 2D SAX feature is used. In the last set of experiment, a weighted sum-rule score fusion is used. The score of the SIFT matching and score of the SAX matching are normalized to *[0, 1]* increasingly before fusion. The weights are empirically chosen as 0.8 for SIFT and 0.2 for 2D SAX.

It can be seen from Figure 7 that comparatively, 2D SAX can achieve better verification performance then the SIFT feature. However, the performance can be obviously improved through score level fusion. Actually, the EER (Equal Error Rate) of SIFT is 2.5% and the EER of 2D SAX is 0.74% and the EER of the fusion method is 0.37%.

Table 1. Verification performances

FAR	*FRR*			
	SAX +SIFT	*Competitive Code [6]*	*Fusion Code[5]*	*Palm Code [8]*
10^{-6}	6.1%	1.1%	6.1%	8.5%
10^{-5}	3.9%	0.9%	4.2%	5.6%
10^{-4}	1.9%	0.6%	2.3%	3.0%
10^{-3}	0.7%	0.5%	0.9%	1.4%
10^{-2}	0.1%	0.3%	0.3%	0.5%
10^{-1}	0.02%	0.2%	0.2%	0.1%
EER	**0.37%**	**0.3%**	0.56%	0.6%

We compare the performance of the proposed fusion method to that of three widely referenced palmprint authentication approaches: *PalmCode* [8], *FusionCode* [5] and *Competitive Code* [6]. The comparison results are shown in Table 1. It can be seen

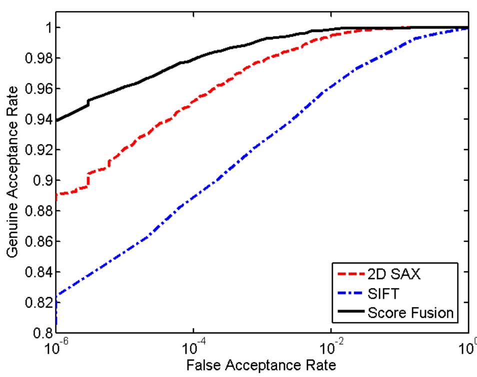

Figure 7. Verification ROC curves

that the proposed fusion method over performs the *PalmCode* and the *Fusion Code* and is comparable to the *Competitive Code*, in terms of EER.

6. Conclusions

In this paper, we have shown the application of SIFT feature in the palmprint authentication. Point-wise matching is used for the SIFT key point matching between palmprints. A simple geometric constraint is employed to remove false matching SIFT point pairs. Also, we have proposed an extension of SAX, a times series technology to 2D images. We have proposed a palmprint authentication approach using 2D SAX. We have shown that through fusion, the SIFT based method can further improve the palmprint authentication accuracy. A C++ language based implementation of our method takes less than one second for the feature extraction and matching for one palmprint image on a Pentium D 3.2 GHz PC. This is fast enough for real time applications. Our future work will concentrate on improving the SIFT performance by developing a better preprocessing step and a better matching stratagem. Actually, It has been revealed that the performance of the SIFT based face authentication can be effectively improved using graph matching [17]. A more refined fusion method is also to be studied.

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