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FUSION OF MULTIPLE FEATURES FOR PALMPRINT AUTHENTICATION

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Abstract:

A palmprint image contains abundant features, such as the ridges, lines and textures, etc. Different features reflect the different characteristic of the palmprint. Fusion of multiple palmprint features may enhance the performance of a palmprint authentication system. In this paper, we investigate the fusion of two novel palmprint representations: orientationCode and diffCode. OrientationCode are defined using four directional templates and diffCode is computed using differential operation. Then these two codes are fused to measure the similarity of palmprints. The experimental results show that the proposed approach can get a very high accuracy.

Keywords:

Biometrics; palmprint authentication; orientationCode; diffCode; feature fusion

1. Introduction

Computer-aided personal recognition is becoming increasingly important in our information society. Biometrics is one of the most important and reliable methods in this field [1]. The most widely used biometric feature is the fingerprint and the most reliable feature is the iris. However, it is very difficult to extract small unique features (known as minutiae) from unclear fingerprints and the iris input devices are very expensive. Other biometric features, such as the face and voice, are less accurate and they can be mimicked easily. The palmprint, as a relatively new biometric feature, has several advantages compared with other currently available features [1]: palmprints contain more information than fingerprint, so they are more distinctive; palmprint capture devices are much cheaper than iris devices; palmprints also contain additional distinctive features such as principal lines and wrinkles, which can be extracted from low-resolution images; a highly accurate biometrics system can be built by combining all features of palms, such as palm geometry, ridge and valley features, and principal lines and wrinkles, etc. It is for these reasons that palmprint recognition has recently attracted an increasing amount of attention from researchers [2-8].

A palmprint contains following basic elements: principal lines, wrinkles, delta points and minutiae, etc. [9]. And these basic elements can constitute various palmprint features. Different palmprint features reflect the different characteristic of a palmprint. Fusion of multiple palmprint features may enhance the performance of palmprint authentication system. In this paper, we first define two novel palmprint features: orientationCode and diffCode using the directional templates and differential operation, respectively, and then fuse them to measure the similarity of palmprints.

When palmprints are captured, the position, direction and amount of stretching of a palm may vary so that even palmprints from the same palm may have a little rotation and translation. Furthermore, palms differ in size. Hence palmprint images should be orientated and normalized before feature extraction and matching. The palmprints used in this paper are from the Polyu Palmprint Database [10]. The samples in this database are captured by a CCD based palmprint capture device [6]. In this device, there are some pegs between fingers to limit the palm's stretching, translation and rotation. These pegs separate the fingers, forming holes between the forefinger and the middle finger, and between the ring finger and the little finger. In this paper, we use the preprocessing technique described in [6] to align the palmprints. In this technique, the tangent of these two holes are computed and used to align the palmprint. The central part of the image, which is 128 × 128, is then cropped to represent the whole palmprint. Such preprocessing greatly reduces the translation and rotation of the palmprints captured from the same palms. Figure 1 shows a palmprint and its cropped image.

The rest of this paper is organized as follows. Section 2 extracts two novel palmprint features. Section 3 fuses multiple features for palmprint similarity measuring. Section 4 contains some experimental results. And Section 5 provides some conclusions.

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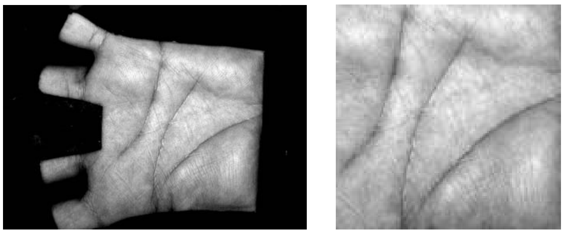


(a) (b)

Figure1. An example of the palmprint and its cropped image: (a) Original Palmprint. (b) Cropped Image

2. Feature Extraction

In this section, we will define two novel palmprint features: orientationCode and diffCode.

2.1. OrientationCode Extraction

We devise several directional templates to define the orientation of each pixel. The 0°-directional template is devised as below:

$$T_{0^\circ} = \begin{pmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 2 & 2 & 2 & 2 & 2 & 2 & 2 & 2 & 2 \\ 3 & 3 & 3 & 3 & 3 & 3 & 3 & 3 & 3 \\ 2 & 2 & 2 & 2 & 2 & 2 & 2 & 2 & 2 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \end{pmatrix} \quad (1)$$

And the α-directional template (T_α) is obtained by rotate T_{0° with Angle α.

Denote I as an image. The magnitude in the direction α of I is defined as

$$M_\alpha = I * T_\alpha \quad (2)$$

where "*" is the convolution operation. M_α is called the α-directional magnitude (α-DM).

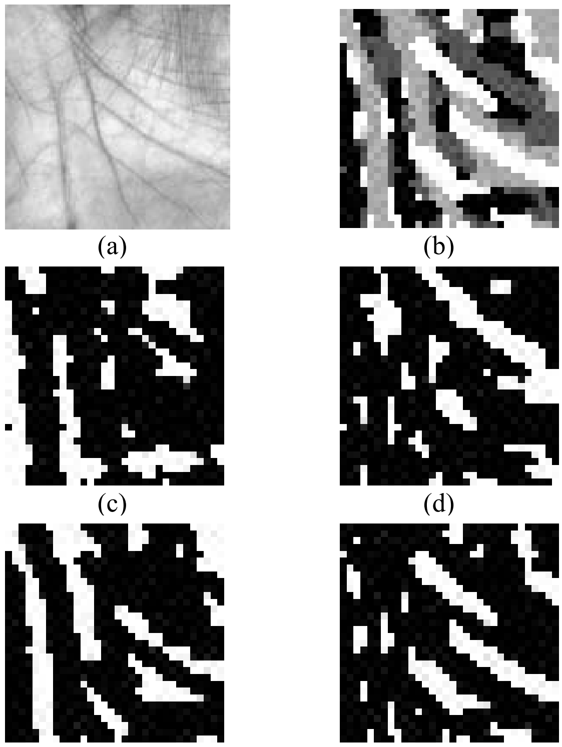
Since the gray-scale of a pixel on the palm lines is smaller than that of the surrounding pixels, which are not on the palm lines, we take the direction in which the magnitude is the minimum as the orientation of the pixel. That is, the orientation of Pixel (i, j) in Image I is computed as below:

$$O(i, j) = \arg\min_{\forall \alpha} M_\alpha(i, j) \quad (3)$$

O is called the OrientationCode of the Palmprint. Four directional templates ($0^\circ, 45^\circ, 90^\circ$ and 135°) are used to extract the OrientationCode in this paper.

The size of the preprocessed palmprint is 128 × 128. Extra experiments show that the image with 32 × 32 is enough for the OrientationCode extraction. Therefore, before compute the orientationCode, we resize the image from 128 × 128 to 32 × 32. Hence the size of the OrientationCode is 32 × 32.

Figure 2 shows an example of the orientationCodes, in which (a) is the original palmprint, (b) is OrientationCode (the different orientations are represented by the different gray scales) and (c)--(f) are the pixels with the orientation $0^\circ, 45^\circ, 90^\circ$ and 135°, respectively. This figure shows that the orientationCode keeps the most information of the palm lines.



(a) (b) (c) (d) (e) (f)

Figure 2. An example of OrientationCode. (a) The original palmprint. (b) OrientationCode; (c)--(f) the pixels with the orientation $0^\circ, 45^\circ, 90^\circ$ and 135°, respectively

Figure 3 shows some examples of the OrientationCodes, in which (a) and (b) are from a palm while (c) and (d) are from another palm, and (e)-(h) are their OrientationCodes. According to this figure, OrientationCodes from the same palms are very similar while the ones from different palms are quite different.

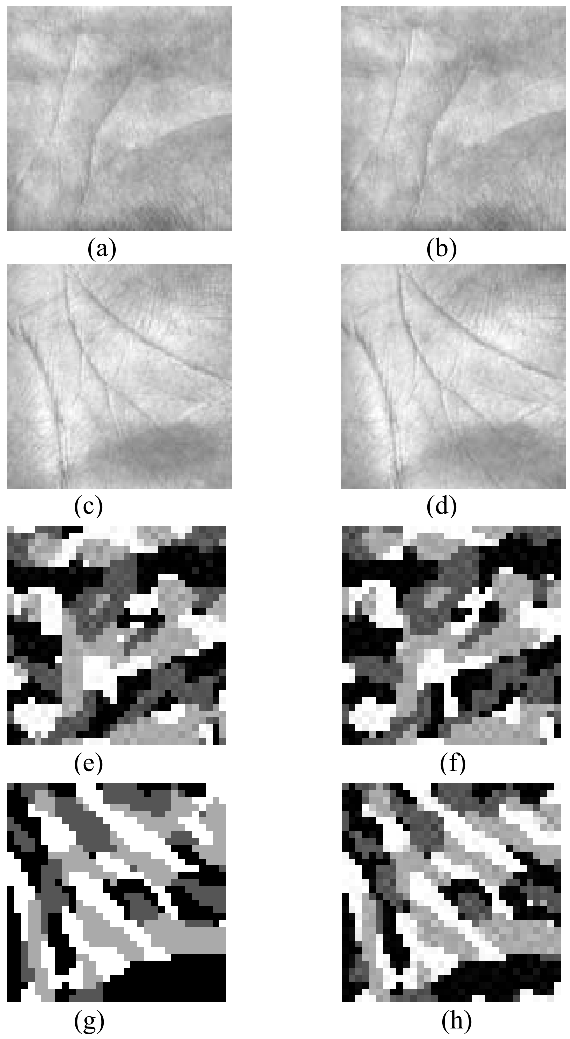


Figure 3. Some examples of the orientationCodes. (a) and (b) are two palmprint samples from a palm; (c) and (d) are two palmprint samples from another palm; (e)-(h) are the OrientationCodes of (a)-(d), respectively

2.2. DiffCode Extraction

Let I denote a palmprint image and G_σ denote a 2D Gaussian filter with the variance σ. The palmprint is first filtered by G_σ as below:

$$I_s = I * G_\sigma \tag{4}$$

where "*" is the convolution operator.

Then the difference of I_s in the horizontal direction is computed as following:

$$D = I_s * b \tag{5}$$

$$b = \begin{pmatrix} -1 & 1 \end{pmatrix} \tag{6}$$

where "*" is the convolution operator.

Finally, the palmprint is encoded according to the sign of each pixel of D:

$$C(i,j) = \begin{cases} 1, & D(i,j) > 0; \\ 0, & \text{otherwise}. \end{cases} \tag{7}$$

C is called the diffCode of the palmprint I. Extra experiments also show that the image with 32 × 32 is enough for the DiffCode extraction. Therefore, before compute the diffCode, we resize the image from 128 × 128 to 32 × 32.

Hence the size of the DiffCode is also 32 × 32. Figure 4 shows some examples of DiffCode.

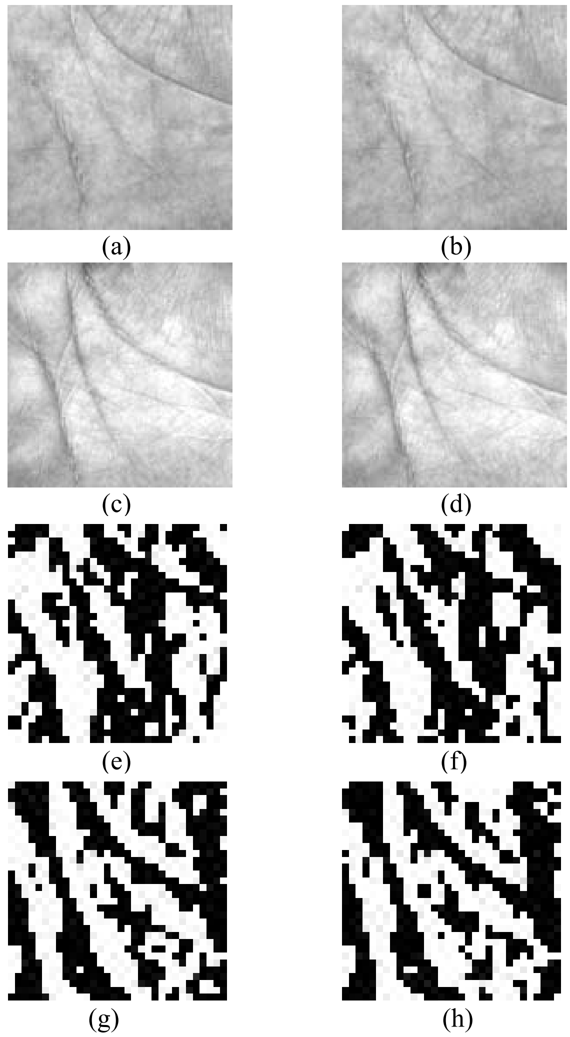


Figure 4. Some examples of the diffCodes. (a) and (b) are two palmprint samples from a palm; (c) and (d) are two palmprint samples from another palm; (e)-(h) are the diffCodes of (a)-(d), respectively

3. Fusion of the orientationCode and diffCode for Similarity Measurement

In this section, we fuse the orientationCode and diffCode to measure the similarity of palmprints.

Let I_1 and I_2 denote two palmprints, O_1 and O_2 denote their orientationCodes, and D_1 and D_2 denote their diffCodes.

For any Point (i, j), if $O_1(i, j) \neq O_2(i, j)$ or $D_1(i, j) \neq D_2(i, j)$, this point is regarded as a different point between I_1 and I_2.

Obviously, if I_1 and I_2 are from the same palm, the number of different points between I_1 and I_2 should be very small.

We construct the difference matrixes O and D to respectively represent the difference between O_1 and O_2, and between D_1 and D_2 as below:

$$O(i, j) = O_1(i, j) \otimes O_2(i, j) \quad (8)$$

$$D(i, j) = D_1(i, j) \otimes D_2(i, j) \quad (9)$$

where "$\otimes$" denote logical *XOR* operator. The non-zero points in O and D respectively indicate that the value of the corresponding pixels in O_1 and O_2, and D_1 and D_2 are different.

Then the difference matrix M containing all different points between I_1 and I_2 can be computed as following:

$$M(i, j) = O(i, j) \mid D(i, j) \quad (10)$$

where "|" denote logical *XOR* operator.

Finally, the similarity of I_1 and I_2 can be defined as below:

$$S(I_1, I_2) = 1 - \frac{\sum_{i=1}^{i=32} \sum_{j=1}^{j=32} M(i, j)}{32 \times 32} \quad (11)$$

Obviously, $S(I_1, I_2)$ is between 0 and 1 and the larger the matching score, the greater the similarity between I_1 and I_2. The matching score of a perfect match is 1. Because of imperfect preprocessing, there may still be a little translation between the palmprints captured from the same palm at different times. To overcome the translation problem, we vertically and horizontally translate O_1 and D_1 with a few points, and then, at each translated position, compute the matching score. Finally, the final matching score is taken to be the maximum matching score of all the translated positions.

4. Experimental Results and Analysis

4.1. Palmprint Database

We employed the PolyU Palmprint Database [10] to test our approach. This database contains 600 grayscale images captured from 100 different palms by a CCD-based device. Six samples from each of these palms were collected in two sessions, where three samples were captured in the first session and the other three in the second session. The average interval between the first and the second collection was two months. Some typical samples in this database are shown in Figure 5, in which the last two samples were captured from the same palm at different sessions. According to this figure, the lighting condition in different sessions is very different.

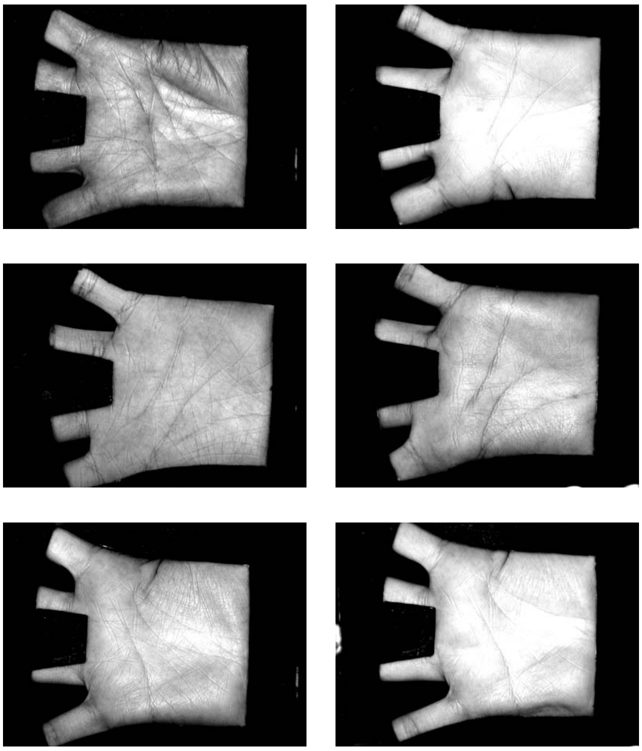


Figure 5. Some typical samples in the Polyu Palmprint Database

4.2. Palmprint Matching

In order to investigate the performance of the proposed approach, each sample in the database is matched against the other samples. The matching between palmprints which were captured from the same palm is defined as a genuine matching. Otherwise, the matching is defined as an impostor matching. A total of 179,700 (600 × 599/2) matching have been performed, in which 1500 matching are genuine matching. Figure 6 shows the genuine and impostor matching scores distribution. There are two distinct peaks in the distributions of the matching scores. One peak (located around 0.6) corresponds to genuine matching scores while the other peak (located around 0.2) corresponds to impostor matching scores. These two peaks are widely separated and the distribution curve of the genuine matching scores intersects very little with that of impostor matching scores. Therefore, the proposed approach can very effectively discriminate between palmprints.

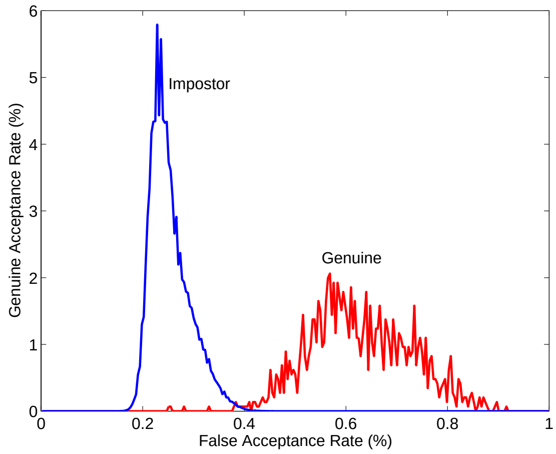


Figure 6. The Distributions of Genuine and Impostor Matching Scores

4.3. Palmprint Verification

Palmprint verification, also called one-to-one matching, involves answering the question ``whether this person is who he or she claims to be" by examining his or her palmprint. In palmprint verification, a user indicates his or her identity and thus the input palmprint is matched only against his or her stored template. To determine the accuracy of the verification, each sample is matched against the other palmprints in the database. If the matching score of the sample palmprint exceeds a given threshold, it is accepted. If not, it is rejected. The performance of a verification method is often measured by the false accept rate (FAR) and false reject rate (FRR). While it is ideal that these two rates should be as low as possible, they cannot be lowered at the same time. So, depending on the application, it is necessary to make a trade-off: for high security systems, such as some military systems, where security is the primary criterion, we should reduce the FAR, while for low security systems, such as some civil systems, where ease-of-use is also important, we should reduce the FRR. To test the performance of a verification method with respect to the FAR and FRR trade-off, we usually plot the so-called Receiver Operating Characteristic (ROC) curve, which plots the pairs (FAR, FRR) with different thresholds [11]. Figure 7 shows the ROC curves of the proposed approach, the diffCode, orientationCode, and PalmCode [6, 12], which were also implemented in the database. According to this figure, the performance of the orientationCode and diffCode are better than that of palmCode, and the fusion of diffCode and orientationCode can greatly improve the accuracy. The EERs of these methods are listed in the Table 1.

Table 1. EERs of Different Palmprint Authentication Methods

Method	EER (%)
PalmCode	0.77
OrientationCode	0.73
DiffCode	0.64
Fusion	0.39

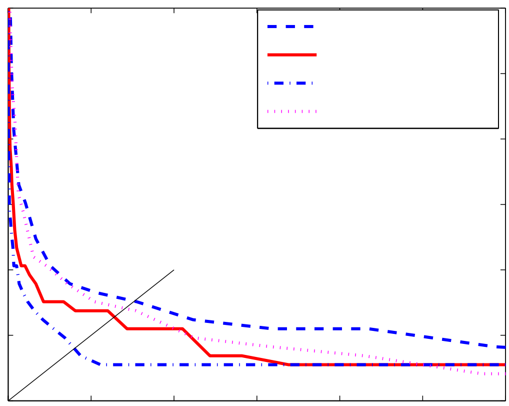


Figure 7. The ROC Curve of the Proposed Approach and the Sobel method

5. Conclusions

Palmprint recognition is a relative new biometric technique for personal recognition. This paper proposes a novel approach for palmprint authentication. In this approach, the diffCode and orientationCode are defined using directional templates and differential operation. And then the similarity of palmprints is measured by fusing these two codes. This approach can get 99.61% accuracy, which can comparable with the existing palmprint authentication methods.

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