Feature-level Fusion for Effective Palmprint Authentication

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Abstract. A feature-level fusion approach is proposed for improving the efficiency of palmprint identification. Multiple Gabor filters are employed to extract the phase information on a palmprint image, which is then merged according to a fusion rule to produce a single feature called the Fusion Code. The similarity of two Fusion Codes is measured by their normalized hamming distance. A database containing 7,752 palmprint images from 386 different palms is used to validate the performance of the proposed method. Empirically comparing our previous non-fusion approach and the proposed method, improvement in verification is ensured

1 Introduction

Biometric personal identification/verification has long been a widely studied topic. Various technologies, including iris, fingerprint, hand geometry, voice, face, signature and retina identification/verification [1-2], have been proposed and developed. Each of the these technologies has its own strengths and weaknesses. Currently, hand-based biometric technologies such as fingerprint verification and hand geometry verification are the most appealing approaches for the biometric identification market. They constitute a total of 60% of total market share as of 2001 [3].

Automatic fingerprint verification is the most mature biometric technology which has been investigated and studied for more than 25 years. Although various scanning technologies, preprocessing, feature extraction and matching algorithms have been proposed for fingerprint verification, there are yet some problems waiting to be resolved. For example, based on the current fingerprint scanning technologies, approximately 1% of people have fingerprints that are almost impossible to be obtained, and 9% of the fingerprints are difficult to capture [4].

Another hand-based biometric technology is hand geometry [3]. It uses geometric information on our hands for personal verification. Based on the simple features of our hands, hand geometry only provides limited accuracy and its ability to distinguish individuality is still an open question [1, 5]. To overcome the problems of the current hand-based biometric technologies, we proposed to use another hand-based biometric, palmprint for personal identification/verification several years ago.

Palmprint, a large inner surface on our hand, contains many line features, for example, principal lines, wrinkles, and ridges. Because of the large surface and the rich line features, we expect palmprints to be robust to noise and to have high individuality. The most promising results developed by us are obtained from a texture-based approach published in [11], which applies Daugman's iris coding scheme [13] to palmprint images. The extracted feature is called PalmCode. In this paper, we propose to use a fusion technique to further improve the coding scheme for palmprint identification.

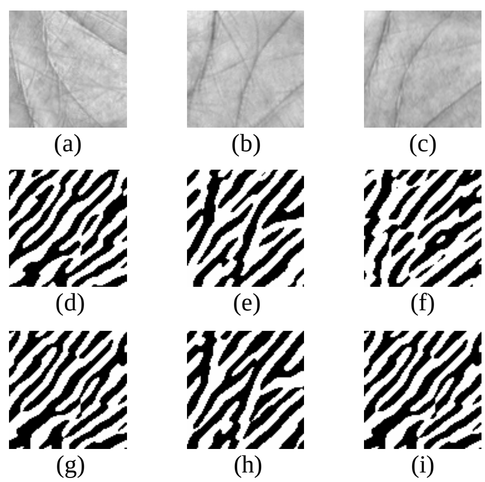

Fig. 1. Three typical samples of PalmCodes: (a)-(c) original images, (d)-(f) real parts of PalmCodes, (g)-(i) imaginary parts of PalmCode

1.1 Motivation

Since the proposed method is developed with reference to PalmCode, we begin our work by a short review about the concept:

1. An adjusted 2-D Gabor filter is applied to the preprocessed palmprint images [11].
2. The signs of the filtered images are coded as a feature vector.
3. Two PalmCodes are measured by the normalized hamming distance.

The detailed implementation of PalmCode and preprocessed palmprint image is mentioned in [11]. Figs. 1(d)-(i) are three PalmCodes derived from the three different palms in Figs. 1(a)-(c). We can observe that the PalmCodes from the different palmprints are similar, which are constituted by many 45^{o} streaks. Intuitively, these structural similarities among PalmCodes from different palms reduce the individuality of PalmCode and the performance of the palmprint identification system.

In this paper, multiple Gabor filters are applied to palmprints and a feature-level fusion technique is introduced to merge the filtered images so as to:

1. destruct the structural similarity among different palmprint features from different palms;
2. increase the individuality among palmprint features from different palms; and
3. increase the performance of our palmprint identification system.

This paper is organized in the following way. Section 2 and Section 3 present the step by step implementation of Fusion Codes and illustrate the comparison of the two Fusion Codes, respectively. Experimental results of the proposed method are given in Section 4. Finally, Section 5 summarizes the main results of this paper and offers concluding remarks.

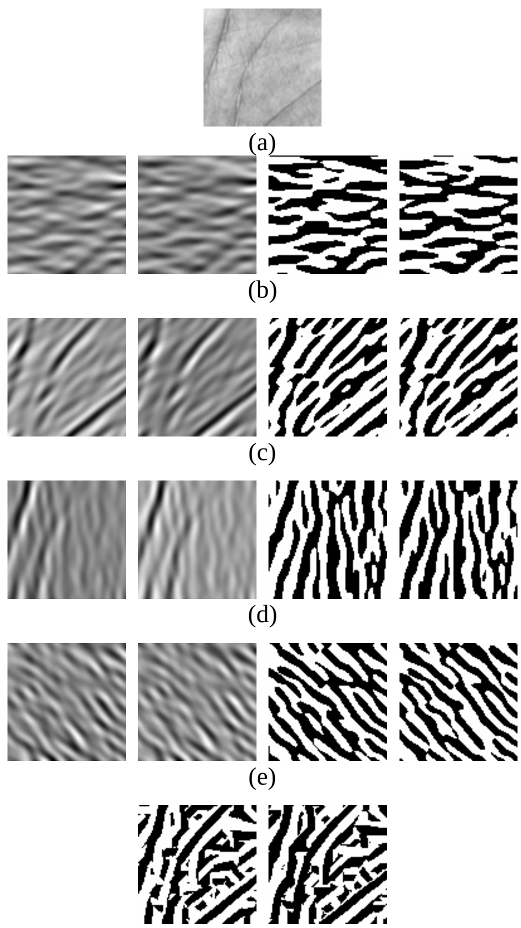

Fig. 2. Procedure of how the Fusion Code is generated: (a) original palmprint image, (b)-(e) real parts (Column 1) and imaginary parts (Column 2) of the filtered images, and real parts (Column 3) and imaginary parts (Column 4) of PalmCodes and (f) Fusion Code

2 Implementation of Fusion Code

First, the preprocessed palmprint image is passed to a circular Gabor filter bank. The filter bank contains four circular Gabor filters, which have the following general formula:

$$G(x, y, q, u, s) = \frac{1}{2ps^{2}} \exp\left\{-\frac{x^{2}+y^{2}}{2s^{2}}\right\} \exp\{2pi(ux\cos q + uy\sin q)\} \quad \textbf{(1)}$$

where, u is the frequency of the sinusoidal wave, q controls the orientation of the function, and s is the standard deviation of the Gaussian envelope. Same as the implementation of PalmCode, the Gabor filters are adjusted to zero DC (direct current). The parameter *?* for the four Gabor filters are 0, p /4, p /2 and 3p /4. The parameters u and s for the four Gabor filters are 0.0916 and 5.6179, respectively. In fact, the PalmCode reported in [11] only uses the Gabor filter with the parameters *?*= p /4, u=0.0916 and s =5.6179. Figs. 2(b)-(e) show the filtered palmprint images and the corresponding PalmCodes. For convenience sake, we use G_j, where j=1,2,3,4 to represent the four Gabor filters.

2.1 Fusion Rule Design and Feature Coding

The filtered images contain two kinds of information: magnitude M_j and phase P_j, which are defined as

$$M_{j}(x, y) = \sqrt{G_{j} * I(x, y) \times \overline{G_{j} * I(x, y)}} \quad \textbf{(2)}$$

and

$$P_{j}(x, y) = \tan^{-1}\left(\frac{i(\overline{G_{j} * I(x, y)} - G_{j} * I(x, y))}{G_{j} * I(x, y) + \overline{G_{j} * I(x, y)}}\right), \quad \textbf{(3)}$$

where "– " represents complex conjugate, "*" is an operator of convolution and I is a preprocessed palmprint image. Because of the zero DC Gabor filters, both of them are independent of the DC of the image. DC replies on the brightness of the capturing environment. In addition to the DC, phase is also independent of the contrast of the image but it is not true for the magnitude. As a result, since the PalmCode only uses the phase information, it is stable for two properties: variations of the contrast, and *DC* of palmprint images. To design a fusion coding scheme inheriting these two properties, we employ the magnitude for fusion and the phase for the final feature. Thus, we propose a fusion rule:

$$k = arg\ max_{j}(M_{j}(x,y)) \quad \textbf{(4)}$$

and coding equations:

$$(h_r, h_i) = (1, 1) \qquad if \qquad 0 \le P_k(x, y) < p/2, \quad \textbf{(5)}$$

$$(h_r, h_i)=(0, 1) \quad \text{if} \quad p/2 \le P_k(x, y) < p\,, \tag{6}$$

$$(h_r, h_i)=(0, 0) \quad \text{if} \quad p \le P_k(x, y) < 3p/2\,, \tag{7}$$

$$(h_r, h_i)=(1, 0) \quad \text{if} \quad 3p/2 \le P_k(x, y) < 2p\,, \tag{8}$$

where h_r and h_i are bits in the real and the imaginary parts of the Fusion Code. A Fusion Code is illustrated in Fig. 2(f).

3. Similarity Measurement of Fusion Codes

In terms of the feature format, the proposed Fusion Code is exactly the same as that of the PalmCode. Thus, the normalized hamming distance for the PalmCode is still useful for the Fusion Code. If we are given two data sets, a matching algorithm would determine the degree of similarity between them. To describe the matching process clearly, we use a feature vector to represent image data that consists of two feature matrices, the real one and the imaginary one. A normalized hamming distance is adopted to determine the similarity measurement for palmprint matching. Let P and Q be two palmprint feature vectors. The normalized hamming distance can be described as:

$$D_o = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} P_M(i,j) \cap Q_M(i,j) \cap \left((P_R(i,j) \otimes Q_R(i,j) + P_I(i,j) \otimes Q_I(i,j))\right)}{2\sum_{i=1}^{N}\sum_{j=1}^{N} P_M(i,j) \cap Q_M(i,j)} \tag{9}$$

where P_R (Q_R), P_I (Q_I) and P_M(Q_M) are the real part, the imaginary part and the mask of P(Q), respectively. The mask is used for denoting the non-palmprint pixels as described in [11]. The result of the Boolean operator ($\otimes$) is equal to zero, if and only if the two bits, $P_{R(I)}(i,j)$, are equal to $Q_{R(I)}(i,j)$. The symbol $\cap$ represents the AND operator, and the size of the feature matrices is $N \times N$. It is noted that D_o is between 1 and 0. For the best matching, the normalized hamming should be zero. Because of imperfect preprocessing, we need to translate vertically and horizontally one of the features and match again. The ranges of the vertical and the horizontal translations are defined from –2 to 2. The minimum D_0 value obtained from the translated matching is considered to be the final matching score.

4 Experimental Results

We collected palmprint images from 193 individuals using our palmprint capture device described in [11]. The subjects are mainly students and staff volunteers from the Hong Kong Polytechnic University. In this dataset, 131 people are male, and the age distribution of the subjects is: about 86% are younger than 30, about 3% are older than 50, and about 11% are aged between 30 and 50. In addition, we collected the palmprint images on two separate occasions, at an interval of around two months. On each occasion, the subject was asked to provide about 10 images each of the left palm and the right palm. Therefore, each person provided around 40 images, resulting in a total number of 7,752 images from 386 different palms in our database. In addition, we changed the light source and adjusted the focus of the CCD camera so that the images collected on the first and second occasions could be regarded as being captured by two different palmprint devices. The average time interval between the first and second occasions was 69 days. The maximum and the minimum time intervals were 162 days and 4 days, respectively.

4.1 Verification

To obtain the verification accuracy of the proposed method, each palmprint image was matched with all of the palmprint images in the database. A matching is counted as a correct matching if two palmprint images are from the same palm. The total number of matching is 30,042,876. None of the hamming distances is zero. The number of comparisons that have correct matching is 74,086 and the rest are incorrect matching. Fig. 3 depicts the corresponding Receiver Operating Characteristic (ROC) curve, which is a plot of the genuine acceptance rate against the false acceptance rate for all possible operating points. In Fig. 3, we can see that our method can operate at a genuine acceptance rate of 98% and a false acceptance rate of 0.01%, with a corresponding threshold 0.36. We also plot the ROC curve of PalmCode for comparison. According to the ROC curves, the performance of Fusion Code is better than that of PalmCode. The verification accuracy of Fusion Code is comparable with previous palmprint approaches [6-12]

5 Conclusion

We have presented a feature-level coding scheme for improving the performance of PalmCode [11], which was the best palmprint identification approach developed by our group. The proposed Fusion Code applies four Gabor filters to the preprocessed palmprint images to compute four PalmCodes. According to the fusion rule, the four PalmCodes are merged to construct Fusion Code. We have proved that Fusion Code is independent of the contrast and the brightness of the palmprint images. The total size of Fusion Code and its mask is 384 bytes, same as that of PalmCode.

In our testing database containing 7,752 palmprint images from 386 different palms, Fusion Code can achieve high genuine (98%) and low false acceptance (0.01%) verification rates, which is comparable with all other palmprint recognition approaches [6-12]. The execution time for the whole process, including preprocessing, feature extraction and final matching, is between 1 and 1.2 seconds on a PC embedded Intel Pentium III processor (500MHz).

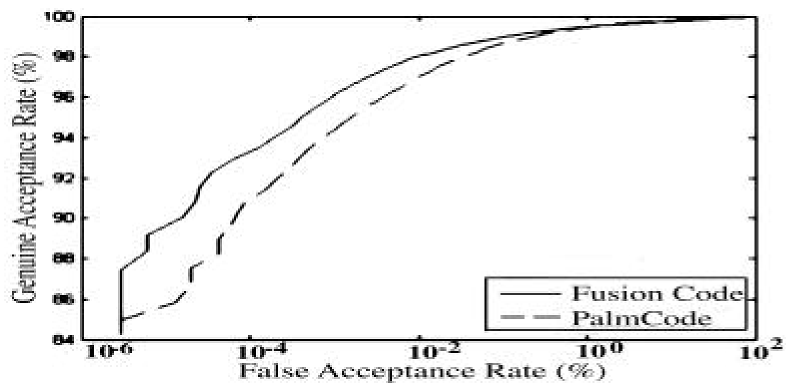

Fig. 3. Verification test results. (a) Genuine and imposter distributions and (b) the receiver operator characteristic curves of Fusion Code and PalmCode

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