Palmprint Texture Analysis Using Derivative of Gaussian Filters*

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Abstract

This paper presents a novel approach of palmprint texture analysis based on the derivative of gaussian filter. In this approach, the palmprint image is respectively preprocessed along horizontal and vertical direction using derivative of gaussian (DoG) Filters. And then the palmprint is encoded according to the sign of the value of each pixel of the filtered images. This code is called DoGCode of the palmprint. The size of DoGCode is 256 *bytes. The similarity of two DoGCode is measured using their Hamming distance. This approach is tested on the PolyU Palmprint Database, which containing* 7605 *samples from* 392 *palms, and the EER is* 0.19%*, which is comparable with the existing palmprint recognition methods.*

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 [1,2]. Within biometrics, the most widely used biometric feature is the fingerprint [3, 4] and the most reliable feature is the iris [2, 5]. However, it is very difficult to extract small unique features (known as minutiae) from unclear fingerprints [3, 4] and the iris input devices are expensive. The palmprint is a relatively new biometric feature. Compared with other currently available features, palmprint has several advantages [6]. Palmprints contain more information than fingerprints, so they are more distinctive. Palmprint capture devices are much cheaper than iris devices. Palmprints contain additional distinctive features such as principal lines and wrinkles, which can be extracted from low-resolution images. By combining all features of palms, such as palm geometry, ridge and valley features, and principal lines and wrinkles, it is possible to build a highly accurate biometrics system.

Many algorithms have been developed for palmprint recognition in the last several years. Han [7] used Sobel and morphological operations to extract line-like features from palmprints. Similarly, for verification, Kumar [8] used other directional masks to extract line-like features. Wu [9] used Fisher's linear discriminant to extract the algebraic feature (called Fisherpalms). The performance of these methods are heavily affected by the illuminance. Zhang [10, 11] used 2-D Gabor filters to extract the texture features (called PalmCode) from low-resolution palmprint images and employed these features to implement a highly accurate online palmprint recognition system. In this paper, we encoded a palmprint using the derivative of gaussian (DoG) Filter. This code is called DoGCode. In the matching stage, the Hamming distance is used to measure the similarity of the DoGCodes.

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 [12]. The samples in this database are captured by a CCD based palmprint capture device [11]. 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 [11] 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

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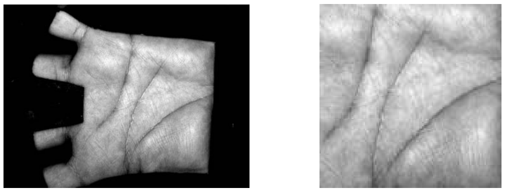
palmprints captured from the same palms. Figure 1 shows a palmprint and its cropped image.



(a) Original Palmprint (b) Cropped Image

Figure 1. An example of the palmprint and its cropped image.

2. DoGCode Extraction

Let I denote a palmprint image and G_σ denote a 2D Gaussian filter with the variance σ. Denote G_{σ_x} and G_{σ_y} as the derivative of G_σ along the x and y directions. The palmprint is first filtered by $G_{\sigma x}$ as below:

$$I_x = I * G_{\sigma_x} \tag{1}$$

$$I_y = I * G_{\sigma_y} \tag{2}$$

where $*$ is the convolution operator.

Then the palmprint is encoded according to the sign of each pixel of I_x and I_y:

$$C_x(i,j) = \begin{cases} 1, & \text{if } I_x(i,j) > 0; \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

$$C_y(i,j) = \begin{cases} 1, & \text{if } I_y(i,j) > 0; \\ 0, & \text{otherwise.} \end{cases} \tag{4}$$

$C = (C_y, C_x)$ is called DoGCode of the palmprint I. The size of the preprocessed palmprint is 128×128. Extra experiments shows that the image with 32×32 is enough for the DoGCode extraction and matching. Therefore, before compute the DoGCode, we resize the image from 128×128 to 32×32. Hence the size of the DoGCode is 32×64. Figure 2 shows some examples of DoGCode.

3 Similarity Measurement of DoGCode

Because all DoGCodes have the same length, we can use Hamming distance to define their similarity. Let $C_1 = (C_{1x}, C_{1y}), C_2 = (C_{2x}, C_{2y})$ be two DoGCodes. The modified Hamming distance of C_1 and C_2, denoted as

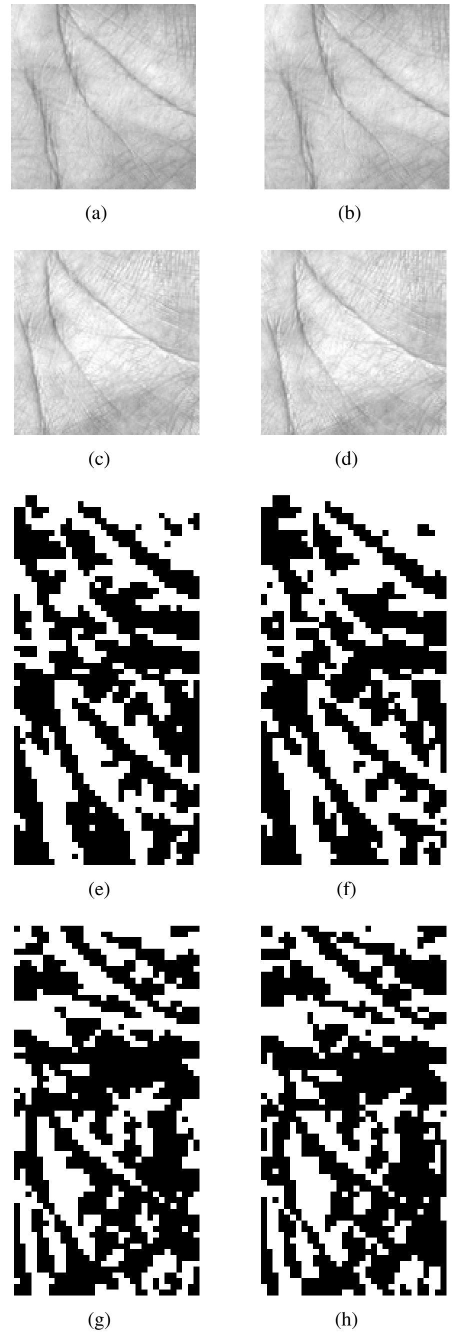


Figure 2. Some examples of DoGCodes. (a) and (b) are two palmprint samples from a palm; (c) and (d) are two palmprint samples from another palm; (e)-(h) are the DoGCodes of (a)-(d), respectively.

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$(H(C_1, C_2))$, is defined as following, i.e.

$$H(C_1, C_2) = \sum_{i=1}^{32}\sum_{j=1}^{32}[(C_{1x}(i,j) \otimes C_{2x}(i,j)) \wedge (C_{1y}(i,j) \otimes C_{2y}(i,j))] \quad (5)$$

where $\otimes$ and $\wedge$ are the logical **XOR** and **AND** operation.

The matching score of two DoGCodes C_1 and C_2 is then defined as below:

$$S(C_1, C_2) = 1 - \frac{H(C_1, C_2)}{32 \times 32} \quad (6)$$

Obviously, $S(C_1, C_2)$ is between 0 and 1 and the larger the matching score, the greater the similarity between C_1 and C_2. The matching score of a perfect match is 1. 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 this problem, we vertically and horizontally translate C_{1x} and C_{1y} a few points to get the translated C_1, and then, at each translated position, compute the matching score between the translated C_1 and C_2. Finally, the final matching score is taken to be the maximum matching score of all the translated positions. Table 1 lists the matching scores between the samples in Figure 2. From this table, the matching scores of the DoGCodes of the palmprints from the same palm are much greater than that from the different palms.

Table 1. The Matching Scores between the DoGCodes in Figure 2

Figure 2	(e)	(f)	(g)	(h)
(e)	1	0.7607	0.3570	0.3419
(f)	-	1	0.3208	0.3258
(g)	-	-	1	0.8448
(h)	-	-	-	1

4 Experimental Results

We employed the PolyU Palmprint Database [12] to test our approach. This database contains 7605 grayscale images captured from 392 different palms by a CCD-based device. These palmprints were taken from people of different ages and both sexes and were captured twice, at an interval of around two months, each time taking about 10 images from each palm. Therefore, This database contains about 20 images of each palm. The images are of two different sizes, 384×284 and 768×568. In our experiments, all images were resized to 384×284 and, using the preprocessing technique described in [11], the central 128×128 part of the image was cropped to represent the whole palmprint. Some typical samples in this database are shown in Figure 3, 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.

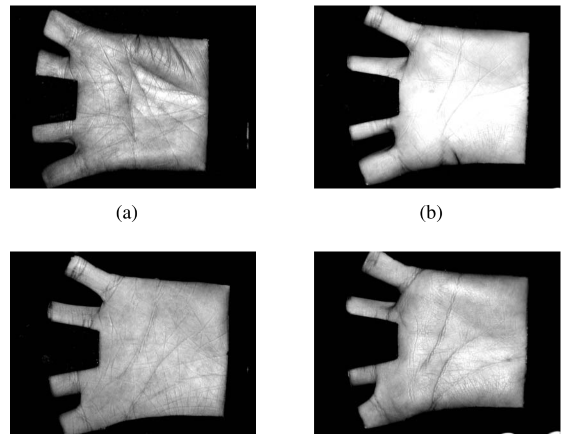
(a) (b) (c) (d)

Figure 3. Some typical samples in the Polyu Palmprint Database.

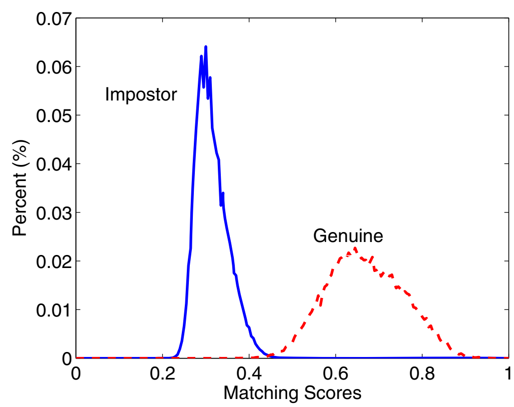

Figure 4. The Distributions of Genuine and Impostor Matching Scores.

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 $28,914,210$ $(7605 \times 7604/2)$

matchings have been performed, in which $141,004$ matchings are genuine matchings. Figure 4 shows the genuine and impostor matching scores distribution. There are two distinct peaks in the distributions of the matching scores. One peak (located around 0.7) corresponds to genuine matching scores while the other peak (located around 0.3) 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.

The Receiver Operating Characteristic (ROC) curve of the proposed approach, which plots the pairs (FAR, FRR) with different thresholds, is shown in Figure 5. For comparisons, the FusionCode method [10], which is an improvement of the PalmCode algorithm [11], is also implemented on this database. In the FusionCode method, each sample is also matched with the others. The ROC curve of the FusionCode method is plotted in Figure 5 and the corresponding equal error rates (EERs) are listed in Table 2. According to the figure, the whole curve of the DoGCode approach is below that of the FusionCode method, which means that the performance of the proposed approach is better than that of the FusionCode method. From Table 2, the EER of the DoGCode approach is 0.19%, which is much smaller than that of FusionCode (0.56%). Furthermore, the size of a DoGCode is $(32 \times 64) \div 8 = 256$ bytes, which is $2/3$ of the size of the FusionCode.

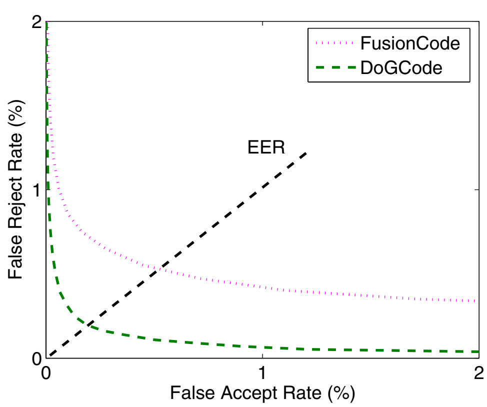

Figure 5. The ROC Curve of the Proposed Approach and FusionCode Method.

5 Conclusion

A novel approach to palmprint authentication is presented in this paper. The palmprint DoGCode is extracted using derivative of gaussian Filters. The similarity of the DoGCode is defined using their Hamming distance. According to the experimental results, the DoGCode approach needs less storage and gets a much higher accuracy than one of the most powerful palmprint recognition method—FusionCode.

Table 2. Comparisons of Different Palmprint Recognition Methods

Method	DoGCode	FusionCode [10, 11]
EER (%)	0.19	0.56
Feature Size (bytes)	256	384

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