Differential Feature Analysis for Palmprint Authentication

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Abstract. Palmprint authentication is becoming one of the most important biometric techniques because of its high accuracy and ease to use. The features on palm, including the palm lines, ridges and textures, etc., are resulted from the gray scale variance of the palmprint images. This paper characterizes these variance using different order differential operations. To avoid the effect of the illumination variance, only the signs of the pixel values of the differential images are used to encode palmprint to form palmprint differential code (PDC). In matching stage, normalized Hamming distance is employed to measure the similarity between different PDCs. The experimental results demonstrate that the proposed approach outperforms the existing palmprint authentication algorithms in terms of the accuracy, speed and storage requirement and the differential operations may be considered as one of the standard methods for palmprint feature extraction.

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]. The palmprint is a relatively new biometric feature and has many advantages for personal authentication [3]. Palmprint recognition is becoming a hotspot in biometrics field.

Han et al. [4] used Sobel and morphological operations to extract line-like features from palmprints. Similarly, for verification, Kumar et al. [5] used other directional masks to extract line-like features. Zhang et al. [6,7] used 2-D Gabor filters to extract the phase information (called PalmCode) from low-resolution palmprint images. Wu et al. [8] extract the palm lines and authenticate persons according to the line structure. Jia et al. [9] used a modified finite Radon transform to compute the line direction of palmprint and employed pixel to region matching for verification. Kong and Zhang [10] defined an orientation for each pixel using a bank of Gabor filters and matched palmprint by compute the angular distance (called CompCode). Sun et al. [11] extract orthogonal line ordinal features (called OrdnCode) to represent palmprint. Up to now, the CompCode and OrdnCode are the most effective algorithms for palmprint authentication.

Different algorithms extract different features from palmprint. Actually, all features on palm, such as palm lines, ridge and textures, etc., are resulted from the gray scale

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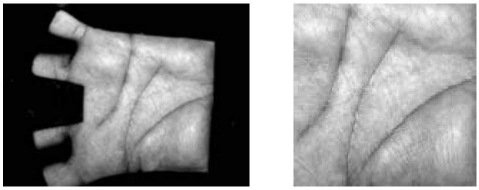


(a) Original Palmprint (b) Cropped Image

Fig. 1. A palmprint and the preprocessed image

variance of the palmprint image. The derivative of an image naturally and effectively reflect these variance, which motivates us to investigate differential feature of palmprint for personal authentication.

The palmprints used in this paper are from the Polyu Palmprint Database [12]. We use the technique in [6] to preprocess a palmprint and crop the central part of the image to represent the whole palmprint. Figure 1 shows a palmprint and its cropped image.

2 Gaussian Derivative Filters (GDF)

Let $G(x, y, \sigma)$ denote a 2-D Gaussian function with variance σ, which is defined as following:

$$G(x, y, \sigma) = \exp\,(-\frac{x^2 + y^2}{2\sigma^2}) \tag{1}$$

The nth-order Gaussian derivative filters (n-GDF) can be obtained by computing the nth-order derivatives of the Gaussian function. For simplification, this paper just considers the derivatives along x and y axis. Therefore, the $1st$ to $3rd$-order Gaussian derivative filters along the x axis are computed as following equations:

$1st$-order GDF:

$$G_{x^{(1)}}(x, y, \sigma) = -\frac{x}{\sigma^2}\exp\,(-\frac{x^2 + y^2}{2\sigma^2}) \tag{2}$$

$2nd$-order GDF:

$$G_{x^{(2)}}(x, y, \sigma) = (-\frac{1}{\sigma^2} + \frac{x^2}{\sigma^4})\exp\,(-\frac{x^2 + y^2}{2\sigma^2}) \tag{3}$$

$3rd$-order GDF:

$$G_{x^{(3)}}(x, y, \sigma) = (\frac{3x}{\sigma^4} - \frac{x^3}{\sigma^6})\exp\,(-\frac{x^2 + y^2}{2\sigma^2}) \tag{4}$$

The different order Gaussian derivative filters along y axis, $G_{y^{(1)}}(x, y, \sigma)$, $G_{y^{(2)}}(x, y, \sigma)$ and $G_{y^{(3)}}(x, y, \sigma)$, can also be computed by exchanging the positions of variable x and y at the right of the above corresponding equations.

3 Palmprint Differential Code (PDC) Extraction

As mentioned above, all features on palms are resulted from the gray scale variance of palmprint images and the derivative is an effective way to capture these variance. We can compute the derivative of a palmprint by convolving it with the corresponding GDF.

Denote I as a preprocessed palmprint image and denote $G_{x^{(k)}}$ and $G_{y^{(k)}}$ as the kth order Gaussian derivative filters. The kth order derivative of I in x and y directions can be computed as following:

$$I_{x^{(k)}} = I * G_{x^{(k)}} \tag{5}$$

$$I_{y^{(k)}} = I * G_{y^{(k)}} \tag{6}$$

where "$*$" is the convolving operation.

To avoid the effect of the illuminance variance, we only use the signs of pixel values of the filtered images to encode the palmprint:

$$C_{x^{(k)}}(i,j) = \begin{cases} 1, \text{ if } I_{x^{(k)}} > 0; \\ 0, \text{ otherwise.} \end{cases} \tag{7}$$

$$C_{y^{(k)}}(i,j) = \begin{cases} 1, \text{ if } I_{y^{(k)}} > 0; \\ 0, \text{ otherwise.} \end{cases} \tag{8}$$

$C = (C_{x^{(k)}}, C_{y^{(k)}})$ is called the kth order palmprint differential code (k-PDC). Figure 2 shows some examples of different order PDCs. This figure demonstrates some properties of the PDCs. The 1-PDCs contain the most prominent features of palmprint, such as the principal lines, but miss most of the details. The 2-PDCs contain both the remarkable features and the most of the palmprint details. Though the 3-PDCs contain more details of the palmprints, they also contain so much noise which can ruin the palmprint features. From these evidences, we can deduce that the higher order PDCs should contain much more noises and cannot be used for palmprint authentication.

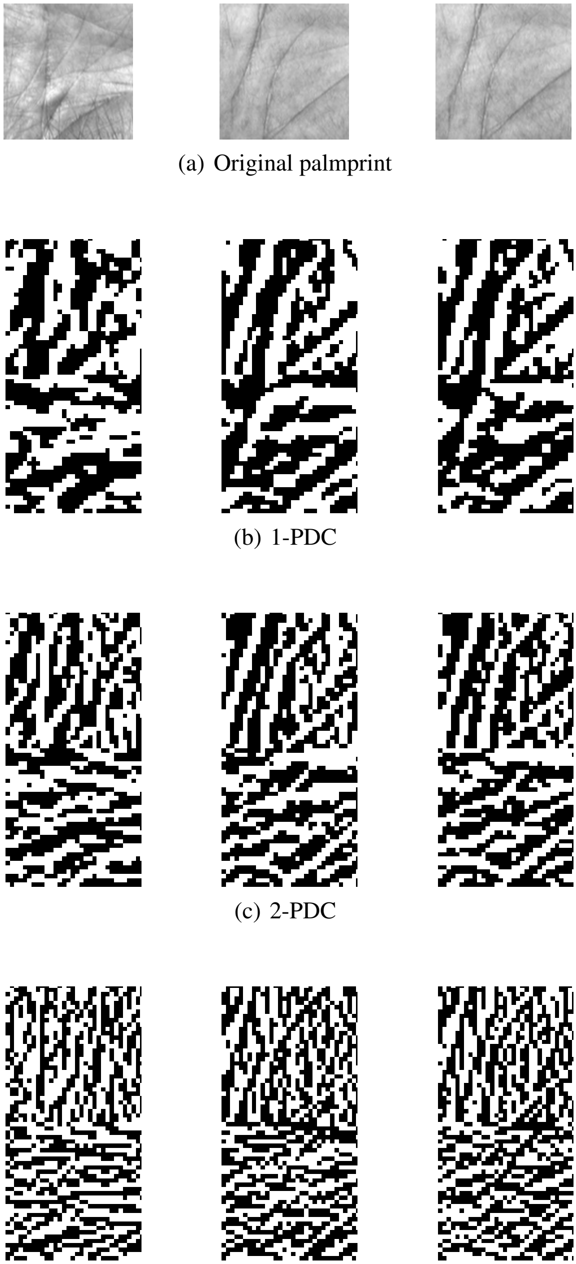
In Figure 2, the last two palmprints are captured from the same palm and the first one is from a different palm. From this figure, we can intuitively find that the PDCs from the same palm are more similar than those from different palm. Therefore, the PDCs can be used to distinguish different palms.

4 Similarity Measurement of PDCs

Denote $C_1 = (C^1_{x^k}, C^1_{y^k})$ and $C_2 = (C^2_{x^k}, C^2_{y^k})$ as the k-PDCs of two palmprint images. The normalized Hamming distance between C_1 and C_2 is defined as following:

$$D(C_1, C_2) = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left[C^1_{x^k}(i,j) \otimes C^2_{x^k}(i,j) + C^1_{y^k}(i,j) \otimes C^2_{y^k}(i,j)\right]}{M \times N} \tag{9}$$

where M and N are the dimension of palmprint image and "$\otimes$" is the logical XOR operation.



(a) Original palmprint

(b) 1-PDC

(c) 2-PDC

(d) 3-PDC

Fig. 2. Some examples of PDC with different order

The similarity between C_1 and C_2 can be measured using a matching score S which computed as following:

$$S(C_1, C_2) = 1 - D(C_1, C_2) \quad (10)$$

Obviously, $0 \leqslant S(C_1, C_2) \leqslant 1$. The larger $S(C_1, C_2)$ is, the more similar C_1 and C_2 are. If C_1 and C_2 are exactly same, which means the perfect matching, $S(C_1, C_2) = 1$. 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_1 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 PDCs shown in Figure 2. From this table, we also can find that the scores between the PDCs from the same palm (> 0.8) are much larger than those from different palms (< 0.6).

Table 1. The matching scores between the PDCs shown in Figure 2

PDC	Column	Left	Middle	Right
1-PDC	Left	1	0.5682	0.5600
	Middle	-	1	0.8452
	Right	-	-	1
2-PDC	Left	1	0.5595	0.5650
	Middle	-	1	0.8169
	Right	-	-	1
3-PDC	Left	1	0.5852	0.5691
	Middle	-	1	0.8218
	Right	-	-	1

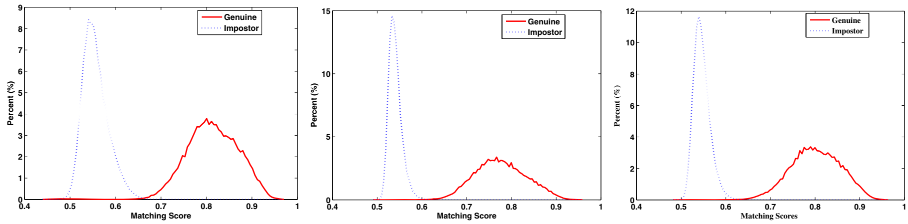
5 Experimental Results and Analysis

5.1 Database

We employed the PolyU Palmprint Database [12] for testing and comparison. This database contains 7752 grayscale images captured from 386 different palms by a CCD-based device. About 20 images are captured from each palm. The size of the images is 384×284 pixels. Using the preprocessing technique described in [6], the central 128×128 part of the image was cropped to represent the whole palmprint.

5.2 Matching Test

To investigate the performance of the proposed approach, each sample in the database is matched against the other samples. Therefore, a total of $30,042,876$ $(7752 \times 7751/2)$ matchings have been performed, in which 74068 matchings are genuine matchings. Figure 3 shows the genuine and impostor matching score distribution of the different order PDCs. There are two distinct peaks in the distributions of the matching score for



(a) 1-PDC (b) 2-PDC (c) 3-PDC

Fig. 3. Matching score distribution

each order PDCs. 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 different order PDCs can effectively discriminate between the palmprints from different palms.

5.3 Accuracy

To evaluate the accuracy of the proposed approach, each sample is matched against the other palmprints and the ROC curves of the different order PDCs are shown in Figure 4. For comparison, the competitive code (CompCode) [10] and ordinal filters (OrdnCode) [11] based method are also implemented and tested on this database. Their ROC curves are also plotted in Figure 4. According to this figure, the 2-PDC's ROC curve is under the curves of the 1-PDC and 3-PDC and the 3-PDC's curve is under that of the 1-PDC. Therefore, among these three order PDCs, the 2-PDC obtains the highest accuracy while the 1-PDC get the lowest accuracy. Also from this figure, the performance of 2-PDC is also better than the CompCode and OrdnCode algorithms. The accuracy of the CompCode algorithm is similar with that of the 3-PDC and the EER of the OrdnCode method is similar with that of the 1-PDC.

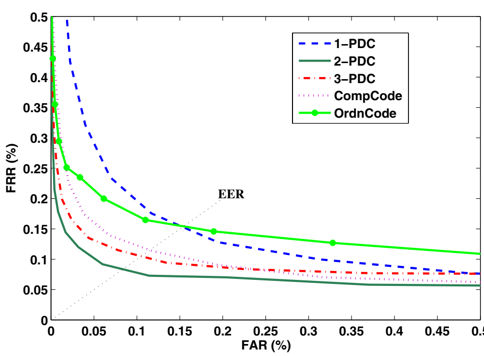


Fig. 4. The ROC curves of different palmprint algorithms

Table 2. Comparisons of different palmprint algorithms

	EER (%)	Feature Size	Extracting Time(ms)	Matching Time(ms)
1-PDC	0.1462	256	9.6	0.09
2-PDC	0.0759	256	10.1	0.09
3-PDC	0.0965	256	10.3	0.09
CompCode	0.1160	384	70	0.18
OrdnCode	0.1676	384	58	0.18

The PDC approach, CompCode algorithm and OrdnCode method are compared in Table 2 in terms of accuracy, feature size and speed. From this table, the proposed PDC approach outperforms other two in all of these aspects.

5.4 Discussion

According to the experimental results, the accuracy of the PDC is higher than the CompCode and OrdnCode, which may be for the following reasons. Both the CompCode and the OrdnCode methods extracted the orientation information of each pixel on the palmprint while the PDC approach captured the grayscale variance tendencies. Obviously, the orientation information is much more sensitive to the rotation of the palm than the grayscale variance tendency. Hence, the PDC approach performs better on the palmprints with some rotation than the CompCode and OrdnCode methods. Although the preprocessing removes most of the rotation between the palmprints of the same palms, there may still remain a little. Therefore, the PDC approach can get a higher accuracy. The proposed approach demonstrates the power of the differential operations for palmprint authentication.

Actually, most of the existing palmprint recognition methods can be looked as the differential operations based methods. Since the Gabor filters can be regarded as the weighted 2nd or 3rd-order Gaussian derivative filters, the Gabor filters based methods, such as CompCode [10], PalmCode [6] and FusionCode [7], etc., can be considered as the differential operations based methods. The orthogonal line ordinal filter used for OrdnCode extraction [11] is a kind of the 1st-differtinal operator. And the Sobel operators based methods [4] are also based on the 1st-differential operations. Therefore, the differential operations may be considered as one of the standard methods for palmprint feature extraction.

6 Conclusions and Future Work

This paper encodes the palmprint image using the different order differential operations. This approach can capture the typical character of the palmprint and can effectively distinguish palmprints from different palms. The 2nd order derivative of palmprint is the most distinguishable. Compared with the existing palmprint methods, the proposed approach can get a higher accuracy with less storage requirement and less response time. The differential operations may be considered as one of the standard methods for palmprint feature extraction.

In the future, we will investigate the PDC with different directions and study the multiscale PDC for palmprint recognition.

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