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Half-orientation extraction of palmprint features ☆

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ABSTRACT

Orientation features of the palmprint are usually used in palmprint recognition methods. Conventional orientation based methods are always based on an assumption that the line in a palmprint is straight and possesses only a single dominant orientation. However, a large number of "lines" in a palmprint are curves. The point in these curves usually has two dominant orientations. Moreover, it can be seen that there are numerous cross wrinkles in a palmprint. The cross point of any two cross wrinkles obviously has two different dominant orientations. In this paper, we proposed a simple and effective double half-orientation based method for feature extraction and recognition of the palmprint. In the method, a bank of "half-Gabor" filters are defined for the half-orientation extraction of a palmprint. Compared with the single dominant orientation, the double half-orientations can more precisely characterize the global orientation feature of a palmprint. Extensive experiments are carried out on three different kinds of palmprint databases and the results show that the proposed method achieves a promising performance in both palmprint verification and identification and outperforms other orientation feature based methods.

1. Introduction

Biometrics, such as personal authentication based on the DNA, face, fingerprint, iris, voice, signature and gait, have been widely studied [1–3]. As a relatively new and novel biometric authentication technology [4,5], palmprint recognition has received more and more attention recently. The palmprint is defined as the inner surface of a palm, which possesses not only fingerprint-like feature such as minutiae points, singular points and texture but also some other special discriminative features such as principal lines, wrinkles and patterns of ridges. As a result, palmprint based recognition has the potential to achieve reliable performance [6–9]. Huang et al. [10] used the principle lines of the palmprints to perform personal verification. Both principal lines and wrinkles were extracted for palmprint authentication in [11].

For people may have similar principal lines, minutiae of the palmprint are also exploited for palmprint identification. For instance, the minutiae of the palmprint were successfully used in matching latent palmprint images for forensic applications [12,13]. Chen et al. [14] designed a palmprint identification algorithm using the hierarchical minutiae of the palmprint. At the same time, increasing research efforts had been directed devoted to the fusion of multiple traits of the palmprint. Dai and Zhou [15] proposed a multi-feature based method, where the principal lines, minutiae points and density map were extracted and fused. Xu et al. [16] designed a fusion method for palmprint identification by combining the left and right palmprints and obtained notable accuracy improvement.

The orientation feature of the palmprint carries very discriminative information. Most of state-of-the-art orientation based coding methods are proposed in recent years. Zhang et al. [17] implemented an online system for palmprint identification. It utilized a normalized 2-D Gabor filter to extract a special orientation feature of palmprint i.e. palmcode and achieved satisfactory performance in a real time application. Since then, different kinds of coding methods were proposed. Kong and Zhang [18] proposed a competitive code method by extracting the dominant orientation of the palmprint, which used six Gabor filters with different orientations to convolve with the palmprint image and the orientation of the filter with maximum filter response is extracted as the dominant orientation. Based on the winner-take-all rule, the robust line orientation code method (RLOC) [19] extracted the principal orientation code of a palmprint using a modified finite radon transform. The fusion code method [20] employed four filters to convolve with a palmprint and binarized the phase of filtering result with the maximum magnitude among four filter responses. Inspired by the competitive code method and sparse representation, Zuo et al. [21] proposed a sparse multiscale competitive code (SMCC) method which used a group of multiscale Gabor filters to extract multiscale orientation features of a palmprint. By comparing filtering results of two orientations, Sun et al. [22]

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employed three incorporated Gaussian filters to extract three bits ordinal codes of a palmprint. Rather than directly encoding the dominant orientation, the binary orientation co-occurrence vector (BOCV) [23] convolved the palmprint image with a set of Gabor filters on six orientations and binarized the signs of all six filter responses. Further, Zhang et al. [6] extended the BOCV namely E-BOCV by filtering out the fragile codes of the BOCV.

In this paper, a simple and efficient half-orientation based coding method is proposed. This work has following contributions. First, a more reasonable orientation representation namely half-orientation representation is exploited. Double half-orientations can better characterize the global orientation feature of a palmprint than the conventional single dominant orientation. Second, a bank of half-Gabor filters are especially defined to extract the double half-orientation codes of a palmprint. Extensive experiments are conducted on three different types of palmprint databases to evaluate the efficiency and effectiveness of the proposed method.

The rest of this paper is organized as follows. Section 2 illustrates the half-orientation of a palmprint. The double half-orientation based method is proposed in Section 3. In Section 4, a series of palmprint recognition experiments are reported. Finally, Section 5 concludes this paper.

2. Double half-orientations of palmprint

The line is the most important and typical feature of a palmprint [4,10]. The extraction algorithm of orientations of lines has been applied for palmprint recognition. By simply coding the orientation feature of a palmprint, a high accuracy of palmprint recognition could be achieved. It is noted that all conventional orientation based methods are based upon an assumption that the lines in the palmprint images are always straight. In other words, only one dominant orientation exists in a "line" of the palmprint. However, in real conditions, it is not hard to see that most lines in a palmprint are curves. Fig. 1 shows an example, from which we can see that the principal lines in a palmprint image are usually curves. The points in these curves usually have two independent and different orientations which are referred to as double half-orientations in this paper. Using the single dominant orientation, as shown in Fig. 1(c), we generally cannot very accurately represent the global orientation feature of the palmprint. In contrast, double half-orientations, which can be extracted by using double half-part-of-filters shown in Fig. 1(d), are more suitable to characterize the global orientation feature of the palmprint. The radian of these curves can be characterized by the combination of both half-orientations. It should be pointed out that the ordinary single dominant orientation is actually a special case of the double half-orientations when both half-orientations are the same.

Carefully observing the palmprint image we can see that there is a number of cross wrinkles in a palmprint, the cross point of which obviously has two dominant orientations that are consistent with these two wrinkles. Fig. 2 shows an example of these kinds of cross wrinkles. As a result, double half-orientations are more precise than the single dominant orientation to represent the orientation feature of these cross points. Based on the above analysis we propose a simple and effective double half-orientation based method for palmprint recognition.

3. Double half-orientation code based method

3.1. Half-Gabor filters

The Gabor filter is one of the most effective tools for orientation extraction of the palmprint. Because it has good properties of the 2-D spectral specificity of textures as well as variation with 2-D spatial position, it is appropriate for feature extraction of the line of the palmprint images [4,17]. In [25], different types of filters, such as Gabor and Gaussian filters, had been compared in orientation feature extraction and the comprehensive experiments demonstrated that the Gabor filter performed better than other filters. In this study, we also apply the Gabor filter to define the half-Gabor filter for extraction of the half-orientation of the palmprint. The real part of the typical circular Gabor filter has the following general form

$$G(x,y,\theta,\mu,\sigma) = \frac{1}{2\pi\sigma^2}\exp\left\{-\frac{x^2+y^2}{2\sigma^2}\right\}\cos\left(2\pi\mu(x\cos\theta+y\sin\theta)\right) \quad (1)$$

where μ is the radial frequency in radians per unit length, θ is the orientation of the Gabor function in radians, and σ is the standard

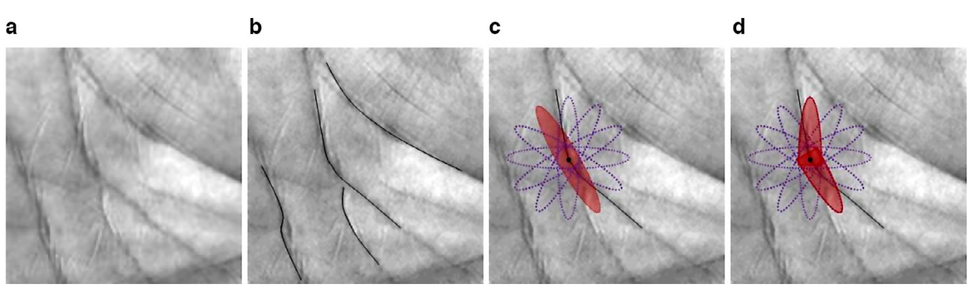

Fig. 1. The line appearance in a palmprint: (a) is an original palmprint image; (b) shows that the principal lines of the palmprint are usually curves; (c) depicts the procedure of the conventional dominant orientation extraction; (d) depicts the procedure of the double half-orientation extraction.

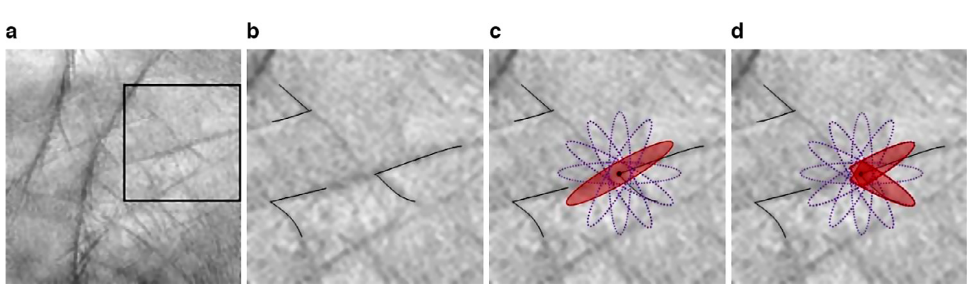

Fig. 2. Cross wrinkles in a palmprint: (a) shows an original palmprint image; (b) shows some cross wrinkles in the palmprint image; (c) depicts the procedure of the conventional dominant orientation extraction; (d) depicts the procedure of the double half-orientation extraction.

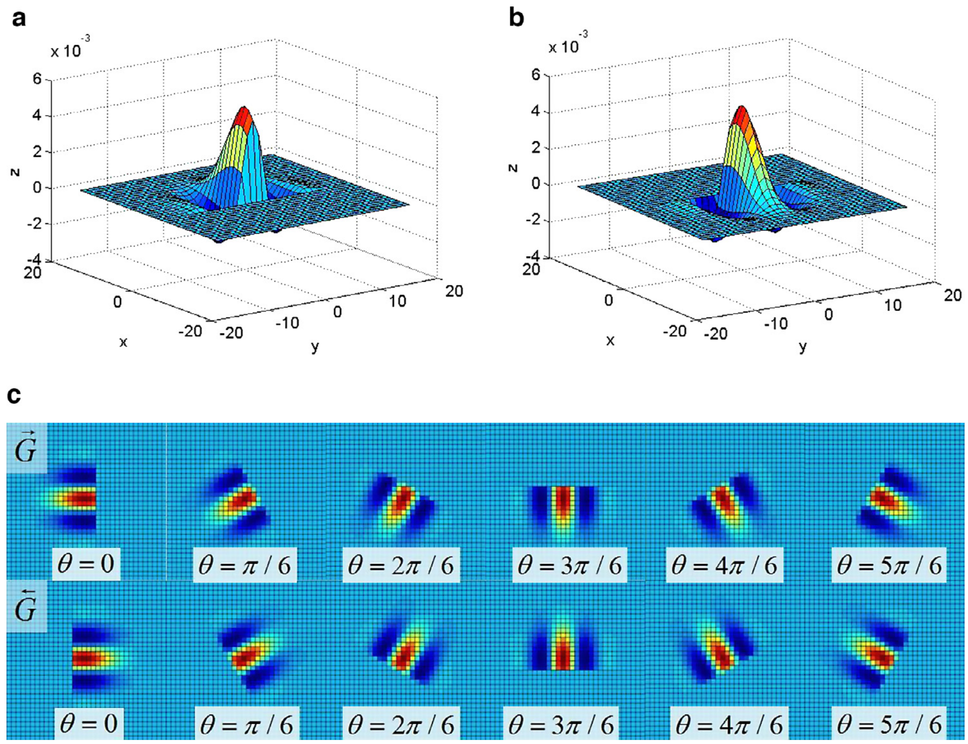

Fig. 3. Appearance of the half-Gabor filters. (a) and (b) are $\vec{G}$ and $\overleftarrow{G}$ with $\theta = 0$, respectively. (c) The planform of half-Gabor filters. The first and second rows are $\vec{G}$ and $\overleftarrow{G}$ with$\theta = j\pi/6$, respectively, where $j = \{0, 1, \ldots, 5\}$.

deviation of the elliptical Gaussian along the x and y axis, respectively. The parameters are empirically set as $\mu = 0.0916$ and $\sigma = 5.6179$ [17]. Jang et al. [27] had proposed a half Gabor filter (HGF) to enhance ridge features of fingerprint, which is defined as the discrete and intersectant masks of the Gabor filter. By contrast, in this paper, a bank of continuous half-Gabor filters are defined as follows:

$$\vec{G}(x, y, \theta, \mu, \sigma) = \begin{cases} G(x, y, \theta, \mu, \sigma) \;\; if \; (-x\sin\theta + y\cos\theta) \geq -T \\ 0 \;\; else \end{cases}, \tag{2}$$

and

$$\overleftarrow{G}(x, y, \theta, \mu, \sigma) = \begin{cases} G(x, y, \theta, \mu, \sigma) \;\; if \; (-x\sin\theta + y\cos\theta) \leq T \\ 0 \;\; else \end{cases}, \tag{3}$$

where T is the size of half-Gabor filter. The size of the Gabor filters are 35×35. Thus, the range of T is from 0 to 17. $\vec{G}$ and $\overleftarrow{G}$ are a group of double half-Gabor filters. Fig. 3 shows the appearance of the half-Gabor filters with $T = 2$.

3.2. Extraction and matching of double half-orientation codes

In the procedure of the double half-orientation code extraction, six groups of double half-Gabor filters with orientations of $j\pi/6(j = 0, 1, \ldots, 5)$ are convolved with the palmprint image. Let $\vec{G}_j$ and $\overleftarrow{G}_j$ be the $\vec{G}$ and $\overleftarrow{G}$ with orientation of $j\pi/6(j = 0, 1, \ldots, 5)$, respectively. The double half-orientation codes of the palmprint are calculated as follows:

$$\vec{P}(x, y) = \arg\max_j \vec{G}_j * I(x, y), \tag{4}$$

and

$$\overleftarrow{P}(x, y) = \arg\max_j \overleftarrow{G}_j * I(x, y), \tag{5}$$

where I is the palmprint image, and "$*$" denotes the discrete convolution. $\vec{P}$ and $\overleftarrow{P}$ are the orientation indices of the $\vec{G}$ and $\overleftarrow{G}$ with the maximum filter response, respectively. We refer to $(\vec{P}, \overleftarrow{P})$ as double-half-orientation codes of the palmprint image and they are jointly represented as $P = (\vec{P}, \overleftarrow{P})$.

Supposing that P and Q are two code planes of the double half-orientations of two palmprint images, the matching score between them is calculated as follows:

$$S(X, Y) = \frac{\sum_{x=1}^{N}\sum_{y=1}^{N} (\vec{P}(x, y) == \vec{Q}(x, y)) + (\overleftarrow{P}(x, y) == \overleftarrow{Q}(x, y))}{2 \times N^2}, \tag{6}$$

where X and Y are the original palmprint images of P and Q, N^2 is the size of the code map, and "$==$" is a "logical equal" operation, the result of which is 1 if the two codes are the same; otherwise, the result is 0. The range of $S(X, Y)$ is from 0 to 1 and a larger $S(X, Y)$ represents a higher similarity between X and Y.

3.3. Analysis of the T

In the definition of the half-Gabor filter, T indirectly defined the size of these half-Gabor filter. Suppose that the size of the Gabor filter is defined as $N \times N$, the range of T is from 0 to $\lfloor N/2 \rfloor$ and the size of the corresponding half-Gabor filter is from $\lceil N/2 \rceil$ to N . The half-orientations of palmprint image extracted by using half-Gabor filter is also associated with the T. Generally speaking, the half-Gabor filter with a small T can extract relatively accurate half-orientation of the palmprint image. Nevertheless, a small T means that only a small part of the Gabor filter is convolved with the palmprint image to extract the orientation feature so as to the extracted half-orientation is sensitive and unstable. In contrast, the half-orientation extracted by using the half-Gabor filter with a larger T should be more robust to the noise and stable. Nevertheless, the extracted half-orientation may deviate from the correct half-orientation feature of the palmprint. For example, when the $T = \lfloor N/2 \rfloor$, the half-Gabor filter is the same as the Gabor filter and the extracted half-orientation of the palmprint is also the same as the orientation feature extracted by using the competitive code method. Therefore, the optimal T should be in some place between 0 and $\lfloor N/2 \rfloor$. In addition, the optimal T is also related to the clarity of the palmprint image. It is believed that, by suitably assigning a T, the half-orientation extracted by using the proposed method could be more discriminative than the competitive code method. Most of the time, the T is set based on experience. In this paper, the T is empirically set as 2 (unless other stated).

4. Experimental results

4.1. Palmprint databases

The PolyU database contains 7,752 palmprint images collected from 386 palms of 193 individuals. Of them, 131 individuals are males and the rest are females. The palmprint images were collected in two sessions with the average interval over two months. In each session, about 10 palmprint images were captured from each palm. So there are 386 classes of palm in the PolyU database, each of which contains about 20 palmprint images. The images in the PolyU database were cropped to a size of 128×128 pixels [17].

The IITD database consists of 2,300 contactless palmprint images from 460 different palms of 230 individuals. In the palmprint images capture, each individual was asked to contribute 5 palmprint images for both the left and right palm. All palmprint images were finally cropped to 150×150 pixels in the IITD database [26]. The T is set as 4 on this database.

The multispectral database includes four independent spectral palmprint databases. Each spectral database was collected from 250 volunteers including 195 males and 55 females. Both palms of every volunteers were asked to provide 12 images under the red, green, blue and near-infrared (NIR) illuminations, respectively. As a result, each spectral database consists of 6000 images of 500 palms. All palmprint images in the multispectral database were cropped into 128 × 128 pixels [28]. The T is set as 6 on the Red and Green database.

Fig. 4 shows some examples of the palmprint images from these three types of palmprint databases. It can be seen that different types of palmprint images show different appearances. For example, the palmprint images in the PolyU database are much clearer than that in the IITD database and the line feature of the palmprint images in the NIR database is not very obvious. In the following experiments, all palmprint images are resized to 64 × 64.

4.2. Distribution of double half-orientation codes

In this section, the discrepancies of the double half-orientation codes of the palmprint images are counted. For each palmprint database, one palmprint image of each palm is selected to conduct the experiments. Since the palmprint images are all normalized to 64 × 64 pixels, $N_{palm} \times 64 \times 64$ pixels, where N_{palm} is the number of palm in a database, are used to calculate the distributions of double half-orientation codes in the database. In the PolyU database, there are 386 palms and thus there are totally $386 \times 64 \times 64 = 1,581,056$ pixels. The test sets include 1,884,160 and 2,048,000 pixels for the IITD and multispectral palmprint databases, respectively. The discrepancy between double half-orientation codes, e.g. $code1$ and $code2$, is calculated as $abs(code1 - code2)$. The range of the discrepancy is from 0 to 5, where the 0 represents that the double half-orientation codes are the same and thus the current point is considered to be in a straight line; otherwise, the double half-orientation codes are different and thus the point is considered to be in a curve. The discrepancy of the double half-orientation codes is shown in Fig. 5. It can be seen that the percentages of the points, of which the double half-orientation codes are the same, on three types of palmprint databases are about 60%, 72% and 40–80%, respectively. In other words, there are a large percentage of points that have two different half-orientation codes in the palmprint images. In addition, from the multiple spectral databases, we note that a larger T relatively increases the percentage of the points that have similar double half-orientations, which is clear for the Red and Green databases. In contrast, a smaller T comparatively decreases the percentage of those points that have similar double half-orientations, which can be seen from the results on the Blue and NIR databases. These observations are consistent with our analysis.

4.3. Palmprint verification

In palmprint verification, the class labels of the palmprint images are known. Each palmprint image is matched with all the other palmprint images in the same database. A match is called as a genuine match if both palmprint images are from the same palm;

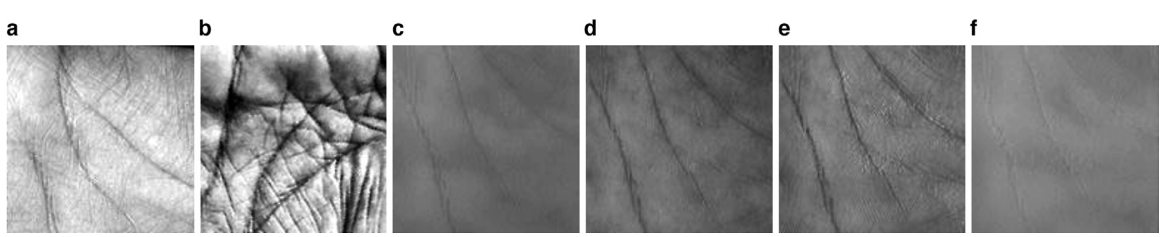

Fig. 4. The palmprint images from three types of palmprint databases: (a) is a palmprint image from the PolyU database; (b) is a palmprint from the IITD database; (c–f) are palmprint images of the same palm from the Red, Green, Blue, and NIR databases, respectively.

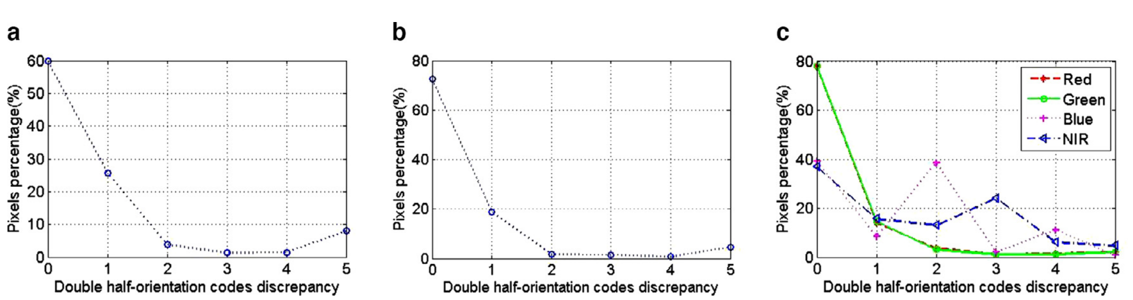

Fig. 5. The distributions of the double half-orientation code discrepancy. (a)–(c) depict the distributions of the double half-orientation code discrepancy on the PolyU, IITD and multispectral databases, respectively.

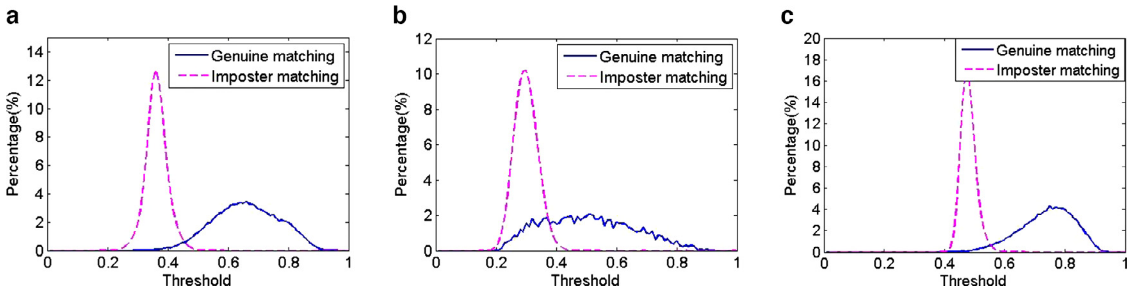

Fig. 6. The distributions of matching scores calculated using the proposed method. (a)–(c) depict the distributions of both the genuine and imposter matching scores on the PolyU, IITD and Red palmprint databases, respectively.

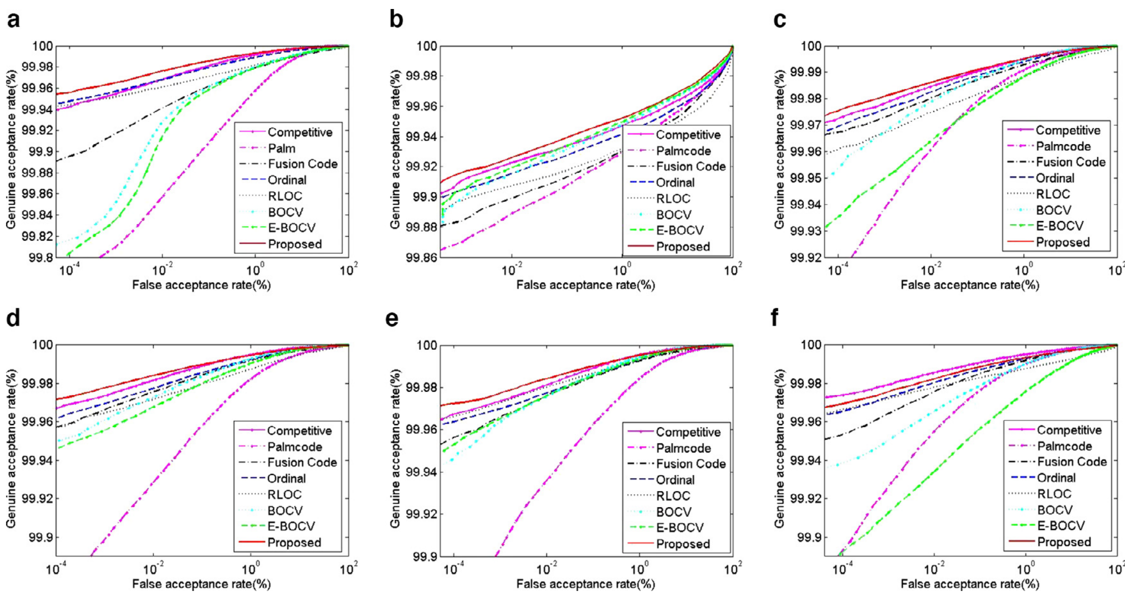

Fig. 7. The ROC curves obtained using different methods on three types of databases. (a)–(f) depict the ROC curves on the PolyU, IITD, Red, Green, Blue and NIR palmprint databases, respectively.

otherwise, the match is considered as an imposter match. In other words, the genuine match is an intra-class comparison and the imposter match is an inter-class comparison. For the PolyU palmprint database, there are 7752 samples in total. So the total number of matches is 30,042,876, of which 74,068 are genuine matches and 29,968,808 are imposter matches, respectively. The IITD database contains 2,643,850 matches including 4600 genuine and 2,369,250 imposter matches, respectively. In each of the multispectral database, the total number of matches is 17,997,000, and the genuine matches and imposter matches are 33,000 and 17,964,000, respectively.

We calculate both the genuine and imposter matching scores using the proposed method. Fig. 6(a)–(c) shows the distributions of the genuine and imposter matching scores on the PolyU, IITD, and Red databases, respectively. The matching scores on other spectral databases have the similar distributions as the Red database. From these distributions we can see that the genuine matching scores are generally larger than the imposter matching scores. A linear classifier is able to effectively distinguish the genuine and imposter matches for the PolyU and multispectral databases. By contrast, the distributions on the IITD database are not as separate as that on the PolyU database. This is probably because that the palmprint images in the IITD database present significant variations on rotation and projection. Nevertheless, the matching scores of imposter matches are also smaller than that of the imposter matches in most cases.

To further evaluate the effectiveness of the proposed method, the genuine and imposter matching scores based on several state-of-the-art orientation based methods are also calculated. Genuine Acceptance Rate (GAR), False Acceptance Rate (FAR) and EER (Equal Error Rate) [17,24] are used to evaluate the performance of the experimental results. The Receiver Operating Characteristic (ROC) curve, which is a graph of GAR versus FAR on all possible decision thresholds in the range of from 0 to 1, is introduced to describe the results of palmprint verification. Fig. 7 depicts the ROC curves of the proposed method and the state-of-the-art orientation based methods, including the competitive code, palmcode, fusion code, ordinal code, RLOC, BOCV and E-BOCV methods, on three types of palmprint databases. From these ROC curves we can see that the proposed method usually achieves a higher GAR against the same FAR than the other methods.

The EERs obtained by using different orientation based methods are shown in Table 1, from which we can see that the proposed method achieves the lowest EER on most palmprint databases. For example, for the PolyU database, the EER achieved by the proposed method is about 0.0204% that is about 21% (0.0261 − 0.0204/0.0261) lower than the lowest EER of the other methods, i.e. 0.0261% of the competitive code method. For the IITD database, the EER of the proposed method is 9% lower than the lowest EER of the other methods. For four spectral palmprint databases, the proposed method is also superior to the other methods on the Red, Green and Blue databases. It is noted that the competitive code method obtains a smaller EER than the proposed method on the NIR database. The most probable reason is that the line feature of the palmprint images in the NIR database is not very obvious. Even so, the EER (0.0139%) obtained by

Table 1
The EERs of different orientation based methods on six palmprint databases (%).

EERs	Competitive code	Palmcode	Fusion code	Ordinal code	RLOC	BOCV	EBOCV	Proposed
PolyU	0.0261	0.0931	0.0899	0.0272	0.0360	0.0469	0.0532	**0.0204**
IITD	0.0696	0.0933	0.0878	0.0744	0.0826	0.0708	0.0671	**0.0633**
Red	0.0145	0.0297	0.0179	0.0161	0.0223	0.0186	0.0313	**0.0131**
Green	0.0168	0.0507	0.0216	0.0202	0.0249	0.0232	0.0303	**0.0144**
Blue	0.0170	0.0463	0.0212	0.0202	0.0203	0.0207	0.0225	**0.0147**
NIR	**0.0137**	0.0332	0.0213	0.0180	0.0208	0.0284	0.0510	0.0139

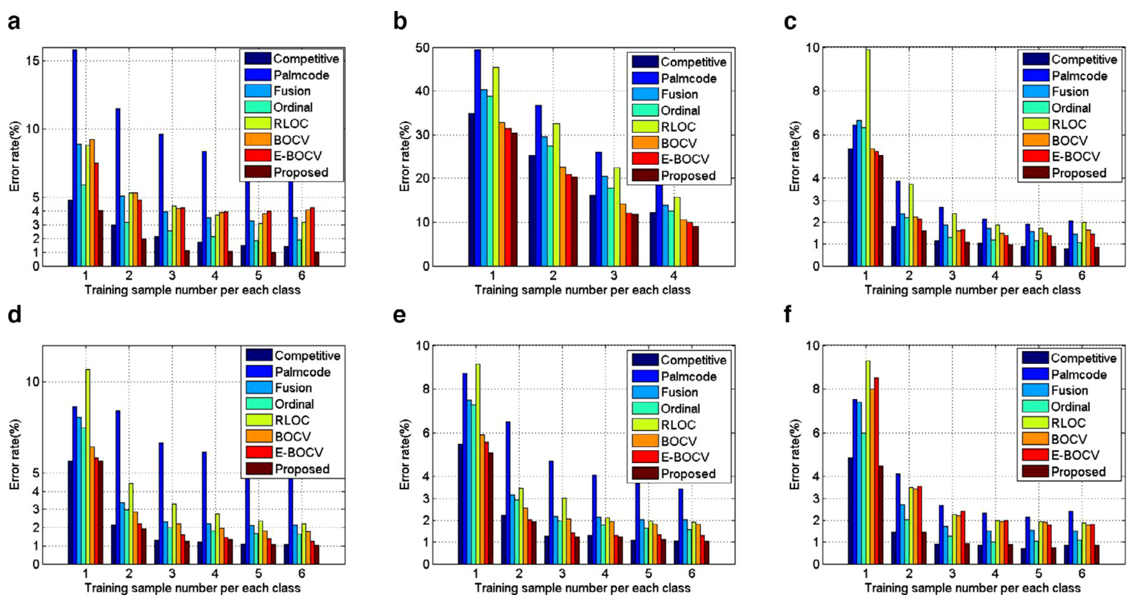

Fig. 8. The error rates of palmprint identification. (a)–(f) depict the error rate on the PolyU, IITD, Red, Green, Blue and NIR databases, respectively.

using the proposed method is still very close to the EER (0.0137%) of the competitive code method.

4.4. Palmprint identification

In palmprint identification, the class labels of a limited amount of palmprint images are known which are used as the training samples and the labels of others are unknown which are referred to the probe samples. Palmprint identification is a one-against-many comparison and tries to predict the class labels of the probe palmprint images. In other words, the probe palmprint images will be compared with all training samples. The probe samples will be classified into the class of the training sample which is the most close to the probe sample. In our paper, the first $N_{train} \in \{1, 2, \ldots\}$ palmprint image(s) of each palm are used as the training samples and then the remaining palmprint images form the probe palmprint set. A probe sample will generate $N_{train} \times N_{palm}$ matching scores in a database, where N_{palm} on three types of palmprint databases are 386, 460 and 500, respectively. In the final decision making, the label of the probe palmprint image is decided as the label of the training sample which produces the minimum matching score. The performance of palmprint identification is estimated by the error rate of the identification. Meanwhile, several state-of-the-art orientation based methods, including the competitive code, palmcode, fusion code, ordinal code, RLOC, BOCV and E-BOCV methods, are also implemented to compare with the proposed method.

To evaluate the performance of the proposed method, we used different number of training images to perform the palmprint identification. Particularly, for each palmprint database, 1 to 6 palmprint images from per palm are used as the training samples and the remaining images form the test set. That is, we run the identification experiments for 6 times with N_{train}= 1 to 6 in each database, respectively. Specially, since there are only 5 palmprint images for each palm in the IITD database, the maximum N_{train} is 4 for the IITD database. The experimental results on six palmprint databases are shown in Fig. 8. It is easy to see that the proposed method achieves lower error rate than other orientation based methods on the PolyU and IITD databases. It is noted that the competitive method performs a litter better than the proposed method on the Green, Blue and NIR databases sometimes. The possible reason is that the palmprint images in these multispectral databases are relative flat and the line features are not distinct. The orientation features extracted by using the competitive code method are relatively robust so as to improve identification accuracy in some special cases. Yet the proposed method is still super the competitive method in most conditions.

4.5. Computational complexity

To evaluate the computational complexity, we compare the computational cost of the proposed method with previous state-of-the-art orientation based methods. All algorithms are implemented using MATLAB 8.1.0 in a PC with double-core Intel(R) i5-3470 (3.2 GHz), RAM 8.00GB, and Windows 7.0 operating system. In order to explicitly demonstrate the computational complexity, the computational time of the feature extraction and matching are computed, respectively. Both the feature extraction and matching are performed for 100 times and the average time taken in each stage using different methods are presented in Table 2. Since the double half-orientation codes of the proposed method are extracted independently, the proposed method spends more time in feature extraction than the competitive code, BOCV and EBOCV methods. Due to the simple matching scheme, the matching speed of the proposed method is slightly faster

Table 2
Computational costs of different orientation based methods in feature extraction and matching.

Methods	Feature extraction (ms)	Matching (ms)
Competitive code	18.837	0.080
Palmcode	1.760	0.204
Fusion code	1.601	0.254
Ordinal code	9.716	0.991
RLOC	65.121	3.712
BOCV	18.896	0.963
E-BOCV	20.746	2.189
Proposed	27.194	0.150

than that of the most methods. The total time cost, e.g. 27.344 ms, is more than several conventional orientation based methods. It is still acceptable for practical applications. It is known that the convolution is the most time consuming part in the extraction of the double half-orientation codes. Nevertheless, only about a half part of filter is exactly used to convolve with a palmprint image in the half-orientation code extraction and the convolution result of another part of filter is always zero. Thus, to speed up the matching time, designing a fast algorithm is feasible for the convolution of a half-Gabor filter with a palmprint image, which is our ongoing work.

5. Conclusions

It is not hard to see that many “lines” in a palmprint are curves and a number of wrinkles of a palmprint are cross lines, which implies that points in a “line” of a palmprint usually have two dominant orientations namely double half-orientations. Statistics confirm that there is a large percentage of points in a palmprint image that have two different half-orientations. In this paper, unlike previous work, a simple and effective double half-orientation based method is proposed for palmprint recognition. Compared with the single dominant orientation, the double half-orientations extracted by using the proposed method can more precisely characterize the global orientation feature of a palmprint. Extensive experimental results show that the proposed method can achieve a competitive performance in palmprint recognition in comparison with the previous state-of-the-art orientation based methods.

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