Local Orientation Binary Pattern with Use for Palmprint Recognition

Lunke Fei[1(✉)], Yong Xu[2], Shaohua Teng[1], Wei Zhang[1], Wenliang Tang[3], and Xiaozhao Fang[1]

[1] School of Computer Science and Technology, Guangdong University of Technology, Guangzhou, China
flksxm@126.com, xzhfang168@126.com, {shteng,weizhang}@gdut.edu.cn

[2] Shenzhen Graduate School, Harbin Institute of Technology, Shenzhen, China
yongxu@ymail.com

[3] School of Software, East China Jiaotong University, Nanchang, China
twlecjtu@163.com

Abstract. In this paper, we extensively exploit the discriminative orientation features of palmprint, including the principal orientation and corresponding orientation confidence, and further propose a local orientation binary pattern (LOBP) for palmprint recognition. Different from the existing binary based representation methods, the LOBP method first captures the principal orientation consistency by comparing the center point with the neighbor sets, and then captures the confidence variations by thresholding the center confidence with neighborhoods so as to obtain orientation binary pattern (OBP) and confidence binary pattern (CBP), respectively. Furthermore, the block-wise statistics of OBP and CBP are concentrated to generate a novel descriptor, namely LOBP, of palmprint. Experiment results on different types of palmprint databases demonstrate the effectiveness of the proposed method.

Keywords: Biometric · Palmprint recognition · Orientation binary pattern · Confidence binary pattern

1 Introduction

As one of relative new and emerging biometric traits, palmprint contains not only the line based features but also the ridge and minutiae points [1–3], which are considered to be immutable and unique to an individual. Therefore, palmprint has been corroborated to have the merits of high distinctiveness, and palmprint based personal authentication has a wide range of civilian, commercial and forensic applications [3].

In past decades, many methods were proposed for low-resolution palmprint recognition. The existing methods of palmprint recognition can be roughly grouped into four categories, including line-based methods, orientation-based methods, subspace-based methods and representation-based methods. The representative work of the line-based methods is generally based on the principal

J. Zhou et al. (Eds.): CCBR 2017, LNCS 10568, pp. 213–220, 2017.
https://doi.org/10.1007/978-3-319-69923-3_23

lines and wrinkles of palmprint [4]. However, the performance of the line-based methods is not very good for the line features of a palmprint are relatively limited. Therefore, the orientation-based methods are developed. Typically, Zhang et al. [5] designed a palmcode method by extracting and coding a certain orientation feature of palmprint. Later, a large number of orientation based coding methods are proposed. The representative methods include the competitive code [6], ordinal code [7], half orientation code (HOC) [8], and discriminative robust competitive code (DRCC) [9] methods. In addition, subspace and representation based classification methods can also be used for palmprint recognition. To sum up, the orientation-based methods are the most popular and competitive in the family of palmprint recognition methods [10].

Recently, the study of local texture representation is very active, and various local texture descriptors have been proposed for image processing. Among them, local binary pattern (LBP) [11] is one of the most powerful one due to its high efficiency and low computation complexity. Extensive works [12] have demonstrated that the LBP based methods are able to achieve reliable performance for image-based recognition. Inspired by that, LBP has begun to use for palmprint recognition [13]. Nevertheless, these methods generally extract LBP on the raw data without extensively considering the characteristics of palmprint. In this paper, we propose a local orientation binary pattern (LOBP) for palmprint recognition. A novel orientation binary pattern is proposed to represent the principal orientation consistency, and a new a confidence binary pattern is designed to describe the changes of the orientation confidence. Further, the block-wise statistical values of OBP and CBP are effectively combined to form a LOBP descriptor. Extensive experiments on three benchmark palmprint databases validate the effectiveness of the proposed method.

The remainder of this paper is organized as follows. Section 2 proposes a local orientation binary pattern for palmprint representation and recognition. Section 3 evaluates the proposed method and presents the experimental results. Section 4 offers the conclusion this paper.

2 Local Orientation Binary Pattern

In this section, we propose a local orientation binary pattern for palmprint representation and recognition.

2.1 Principal Orientation and Orientation Confidence of Palmprint

The basic principle of orientation feature extraction is using a group of line detectors with different orientations to detect the principal orientation of palmprint. Typically, the Gabor filter is one of the most powerful tool for palmprint orientation detection, which has the following general form:

$$G(x, y, \theta, \mu, \sigma, \beta) = \frac{1}{2\pi\sigma\beta} exp[-\pi(\frac{x^2}{\sigma^2} + \frac{y^2}{\beta^2})]exp(i2\pi\mu(xcos\theta + ysin\theta)), \quad (1)$$

where $i = \sqrt{-1}$, μ is the radial frequency in radians per unit length, σ and β are the standard deviations of the elliptical Gaussian along the x and y axis, respectively. According to the experiences of [5], the optimal parameters in Eq. (1) are set as $\mu = 0.0916$, $\sigma = \beta = 5.6179$, and the sizes of the Gabor filter, that is the ranges of x and y, are defined as 35×35. θ defines the orientation of the Gabor function. In this paper, six different orientations, that is $(j-1)\pi/6 (j = 1, 2, ..., 6)$, are used so as to define six templates. In palmprint principal orientation extraction, the real parts of the Gabor filters are convolved with a palmprint:

$$c_j(x, y) = G_j^r \otimes (255 - I(x, y)), \tag{2}$$

where G_j^r represents the real part of the Gabor filter with the orientation of $(j-1)\pi/6$, "$\otimes$" is the convolution operator, I represents an input palmprint image, and c is the corresponding convolved result between the Gabor templates and the input palmprint. Based the convolved results, the principal orientation of palmprint can be obtained as follows:

$$o(x, y) = arg \max_j c_j(x, y). \tag{3}$$

Intuitively, the convolved results on the principal orientation essentially reflects the significance and stability of the orientation. Therefore, we treat the maximum convolved result, that is $c_{o(x,y)}(x, y)$, as the confidence of the principal orientation, which can be obtained as:

$$c_o(x, y) = c_{o(x,y)}(x, y) = arg \max_c c_j(x, y). \tag{4}$$

2.2 LOBP

It is seen that $o(x, y)$ and $c_o(x, y)$ essentially reflect the orientation features of a palmprint. In other words, $o(x, y)$ represents the principal direction, and the corresponding $c_o(x, y)$ reflects the confidence of the principal direction. Therefore, we propose to encode and combine both the principal orientation and the orientation confidence for palmprint representation and recognition.

Given a line of a palmprint, the points along the line within a small local region generally have similar principal orientation, which is the orientation of the line. By contrast, the other points within the local region are not on this line, which possibly leads to different principal orientations. Therefore, the relationship of the principal orientations within a small patch essentially reflects the orientation change trend. The relationship of the principal orientation within a local neighbor area can be represented as follows.

$$OBP = \sum_{i=1}^{8} e(o_i, o_c) 2^i, \tag{5}$$

where o_c is the principal orientation of a central pixel, and o_i denotes the principal orientation of the neighbor pixels. In this paper, the neighbor region is empirically defined as the (8,1) neighbor sets [11], that is, the central point is compared with the most nearest eight points. $e(u, v)$ is 1 when u equals to v, and 0 otherwise.

The maximum convolved results on the principal orientation, that is $c_o(x, y)$, essentially represent the confidence of the principal orientation. The difference of c_o within a (8,1) neighboring patch can capture the orientation confidence variances, which can represented as:

$$CBP = \sum_{i=1}^{8} s(c_{o,i} - c_{o,c})2^i, \tag{6}$$

where $c_{o,c}$ and $c_{o,i}$ denotes the orientation confidence of a central pixel and corresponding neighboring point, respectively. $s(u)$ is 1 when $u > 0$, and 0 otherwise. Unlike conventional LBP, CBP is based on the convolved results, which should be more stable and robust than using the raw data.

Since $o(x, y)$ and $c_o(x, y)$ carry highly correlated information, OBP should be combined with CBP. In general, different areas of a palmprint usually have different line and texture feature so as to carry different orientation features. Therefore, we propose to use block-wise statistics of the OBP and CBP to form a global palmprint descriptor. Specifically, given a palmprint image, we uniformly divided it into a set of non-overlapping blocks, the sizes of which are empirically set to 16×16 pixels. For each block, the principal orientation and corresponding confidence are respectively extracted so as to obtain the OBP and CBP maps, and further to compute the histograms of OBP and CBP, respectively. After that, we concentrate the block-wise OBP based histogram and CBP based histogram to obtain a global histogram of the palmprint, which is named as the local orientation binary pattern (LOBP). Figure 1 shows the framework of our proposed LOBP method.

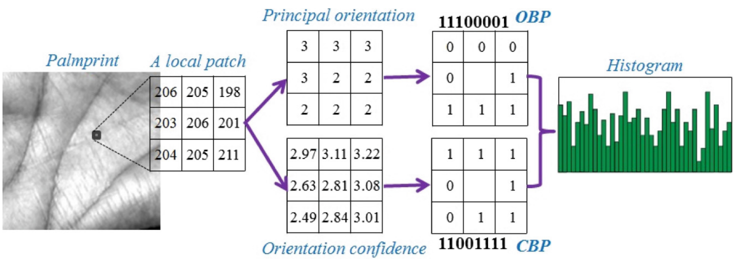

Fig. 1. The basic idea of the LOBP method.

2.3 LOBP Based Palmprint Matching

Given two compared palmprint images, the LOBP based descriptors of them are first calculated. Then, the simple and effective Chi-square distance is employed to determine the similarity of them as follows.

$$\chi^2(P,Q) = \sum_{i=1}^{N_m} \frac{(p_i - q_i)^2}{p_i + q_i}, \tag{7}$$

where P and Q denote two LOBP descriptors of two palmprint images, and p_i and q_i are the value of P and Q at the $i-th$ bin, respectively.

3 Experiments

In this section, we evaluate the effectiveness of the LOBP method on three widely used palmprint databases.

3.1 Palmprint Databases

The PolyU palmprint database contains 7,752 palmprint images, which were captured from 193 different individuals, and a palm provided about 20 samples. The PolyU database is available at "http://www4.comp.polyu.edu.hk/~biometrics/".

The multispectral palmprint database includes four palmprint databases, including the Red, Green, Blue, and NIR palmprint databases. Each database consists of 6,000 samples corresponding to 250 individuals for both the left and right palms, and each palm provides 12 palmprint images. In this study, we adopt the Green spectral palmprint database, referred as M_Green database, to conduct the experiment. The M_Green database can be downloaded at "http://www.comp.polyu.edu.hk/~biometrics/".

The IITD palmprint database consists of 2,601 palmprint images corresponding to 230 subjects with 460 palms, each of which provided 5 to 6 samples. The IITD database is available at "http://www4.comp.polyu.edu.hk/~csajaykr/IITD/".

3.2 Palmprint Verification

Palmprint verification [5] is a procedure of one-to-one palmprint matching, which answers the question that whether a query palmprint is from the same palm of a gallery palmprint. A palmprint matching is called as a genuine match when the query palmprint is from the same palm as the gallery palmprint; otherwise, the comparison is considered as an impostor match. In other words, a genuine match is an intra-class comparison and an impostor match represents an inter-class comparison.

In palmprint verification experiments, a palmprint image in a database will be matched with all other samples using the LOBP method. Then, we calculate the False Acceptance Rate (FAR) and Genuine Acceptance Rate (GAR), and further draw the ROC curve. Moreover, the conventional state-of-the-art methods, including the competitive code [6], ordinal code [7], BOCV [14], E-BOCV [15], HOC [8] and DRCC [9] methods, are also implemented to compare the proposed LOBP method. The ROC curves drawn based on different methods are

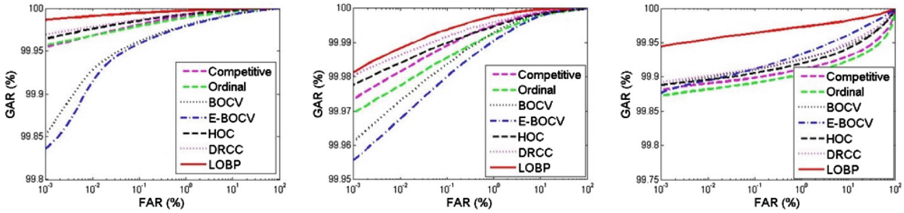

Fig. 2. ROC curves obtained based on different methods on the PolyU, M_Green, and IITD databases, respectively.

shown as in Fig. 2. It is seen from the figure that the proposed method always obtain a higher GAR than other methods on a certain FAR on three palmprint databases. Therefore, the proposed method can achieve the smallest Equal Error Rate (EER) among all methods. In addition, we also test the LBP method on palmprint recognition. However, the result is a very bad, and thus not included in this paper.

It is worth mentioning that the proposed method performs much better than other methods on the IITD database. The possible reason is that the palmprint images of IITD database present serious variances on projection, rotation and translation. The LOBP method generally based on the differences of the center points within neighbor sets, which effectively improve the robustness to the illumination changes.

3.3 Palmprint Identification

Palmprint identification [8] is the process of one-against-many palmprint comparison, which answers the question that which palm of a query palmprint image is from. In general, some palmprint images with already known labels are selected as the training samples in advance. Then, a query palmprint image is compared with all the training samples, and find out the label of the most similar training sample with the query sample. In our experiments, we randomly determine $n(n = 1, 2, 3, 4)$ palmprint images from a palm as the training samples, and correspondingly use the rest palmprint images as the query samples. In the experiment, we employ the rank-1 identification accuracy to measure the performance of palmprint identification. Also, the representative methods, including the competitive code, ordinal code, BOCV, E-BOCV, HOC and DRCC methods, are run and compared with the LOBP method. In addition, all cases are performed for 5 times, and the mean identification accuracies are reported. The comparative experimental results on different palmprint databases are summarized as Fig. 3. It is seen that, with the same situation, the proposed method can achieve the highest accurate rate among all methods.

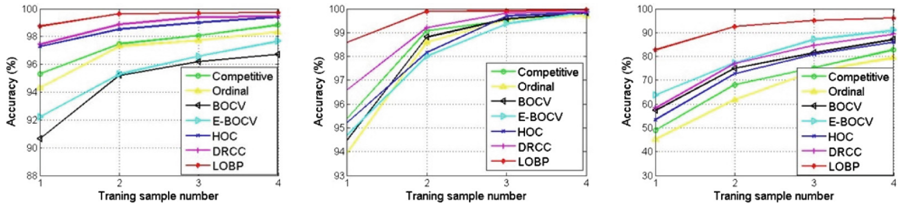

Fig. 3. Accuracy (%) of palmprint identification with using different methods on the PolyU, M_Green, and IITD databases, respectively.

3.4 Comparison of OBP and CBP

To verify the effectiveness OBP and CBP, we perform palmprint verification with using single OBP and single CBP, respectively. Specifically, we respectively use the block-wise histograms of OBP and CBP to form two kinds of palmprint descriptors, and the Chi-square distance is used in the matching stage. The ROC curves of using OBP descriptor and CBP descriptor on three palmprint databases are respectively shown in Fig. 4, in which the ROC curve of LOBP is also included. From the comparative results, we can see that the LOBP performs better than both the OBP and CBP. Therefore, combining the OBP with CBP, that is LOBP, can effectively improve the performance of palmprint recognition.

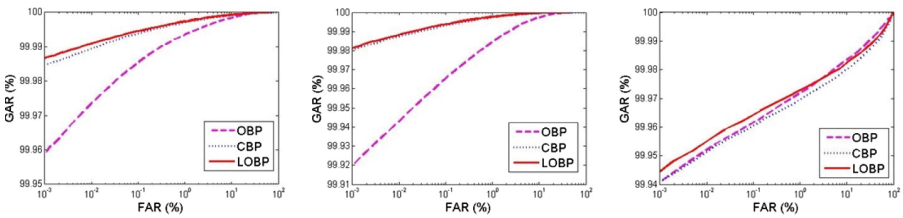

Fig. 4. The ROC curves obtained based on the OBP, CBP and LOBP on the PolyU, M_Green, and IITD databases, respectively.

4 Conclusions

In this paper, for exploiting the principal orientation features and corresponding orientation confidence, a novel local orientation binary pattern (LOBP) is proposed for palmprint recognition. Specifically, the principal orientation is compared within the neighboring sets to obtain the orientation binary pattern (OBP), and the orientation confidence is binarized by thresholding within a local patch to obtain the confidence binary pattern (CBP). The block-wise histograms of OBP and CBP are combined to form the LOBP of palmprint. Extensive experimental results on three widely used palmprint databases have demonstrated the effectiveness of the proposed method.

Acknowledgment. This paper is partially supported by Guangdong Province high-level personnel of special support program (No. 2016TX03X164), and Shenzhen Fundamental Research fund (JCYJ20160331185006518).

References

1. Jia, W., Zhang, B., Lu, J., Zhu, Y., Zhao, Y., Zuo, W., Ling, H.: Palmprint recognition based on complete direction representation. IEEE Trans. Image Process. **26**(9), 4483–4498 (2017)
2. Fei, L., Zhang, B., Xu, Y., Yan, L.: Palmprint recognition using neighboring direction indicator. IEEE Trans. Hum.-Mach. Syst. **46**(6), 787–798 (2016)
3. Jain, A.K., Feng, J.: Latent palmprint matching. IEEE Trans. Pattern Anal. Mach. Intell. **30**, 1032–1047 (2009)
4. Huang, D.S., Jia, W., Zhang, D.: Palmprint verification based on principal lines. Pattern Recogn. **41**, 1316–1328 (2008)
5. Fei, L., Xu, Y., Tang, W., Zhang, D.: Double-orientation code and nonlinear matching scheme for palmprint recognition. Pattern Recogn. **49**, 89–101 (2016)
6. Kong, A.K., Zhang, D.: Competitive coding scheme for palmprint verification. In: 17th International Conference on Pattern Recognition, pp. 520–523 (2004)
7. Sun, Z., Tan, T., Wang, Y., Li, S.: Ordinal palmprint represention for personal identification. In: IEEE Conference on Computer Vision and Pattern Recognition, pp. 279–284 (2005)
8. Fei, L., Xu, Y., Zhang, D.: Half-orientation extraction of palmprint features. Pattern Recogn. Lett. **69**, 35–41 (2016)
9. Xu, Y., Fei, L., Wen, J., Zhang, D.: Discriminative and robust competitive code for palmprint recognition. IEEE Trans. Syst. Man Cybern.: Syst. (2016). doi:10.1109/TSMC.2016.2597291.
10. Zhang, D., Zuo, W., Yue, F.: A comparative study of palmprint recognition algorithms. ACM Comput. Surv. **44**, 1–37 (2012)
11. Ojala, T., Pietikainen, M., Maenpaa, T.: Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. IEEE Trans. Pattern Anal. Mach. Intell. **24**, 971–987 (2002)
12. Huang, D., Shan, C.F., Ardabilian, M., Wang, Y.H.: Local binary patterns and its application to facial image analysis: a survey. IEEE Trans. Syst. Man Cybern. Part C (Appl. Rev.) **41**, 765–781 (2011)
13. Michael, G., Connie, T., Teoh, A.: Touch-less palm print biometrics: novel design and implementation. Image Vis. Comput. **26**, 1551–1560 (2008)
14. Guo, Z., Zhang, D., Zhang, L., Zuo, W.: Palmprint verification using binary orientation co-occurrence vector. Pattern Recogn. Lett. **30**, 1219–1227 (2009)
15. Zhang, L., Li, H., Niu, J.: Fragile bits in palmprint recognition. IEEE Sig. Process. Lett. **19**, 663–666 (2012)