A Fast Robustness Palmprint Recognition Algorithm*

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Abstract. We propose a novel fast robustness palmprint recognition algorithm based on the Curvelet transform and local histogram of oriented gradient (CLHOG) for the poor curve and direction description in the traditional wavelet transform. Curvelet transform is firstly used to obtain four images with the different scales. Then, an algorithm based Local Histogram of Oriented Gradient (LHOG) is designed to extract the robust features from those different scale images. Finally, a Chi-square distance is introduced to measure the similarity in the palmprint features. The experimental results obtained through using the proposed method on both PolyU and CASIA palmprint databases are robust and superior in comparison to some high-performance algorithms.

Keywords: Palmprint recognition, Curvelet, Local Histogram of Oriented Gradient, chi-square distance.

1 Introduction

Palmprint recognition, as a branch of biometric research, gradually becomes a hotspot in recent years [1-3]. Most palmprint recognition methods are discussed in frequency domain, such as wavelet transform. What's more, it has obtained the better identification. HAFIZ et al [4] proposed wavelet-based dominant feature extraction algorithm for palmprint recognition. However, wavelet can only describe characteristics in the local region or singular points, and fail to represent multi-directional edge, texture and other geometric properties of two-dimension images. Therefore, it cannot be an optimal selection for palmprint [4-5]. Zhou et al [5] proposed face recognition algorithm based on adaptive local Gabor algorithm of energy. But a larger feature dimension can limit the real-time requirement. So they reduced the dimension using principal component analysis (PCA) to deal with this problem, while the recognition accuracy still needed further improvement.

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Later on, Wang et al [6] designed a novel palmprint identification based on Curvelet transform decision fusion. Curvelet transform has a good description for curve. Also, each layer image from the Curvelet transform can show the direction information clearly. But, it seldom considers the main orientation, namely, the orientation trend for palmprint image. In order to solve the problem, we propose a fast robustness palmprint recognition algorithm based on Curvelet local histogram of oriented gradient (CLHOG), which can not only obtain a desirable recognition result, but also meet real-time requirement. After simple preprocessing, we need to decompose palmprint into four layers by Curvelet transform and extract the direction histogram for the local palmprint image by local histogram of oriented gradient (LHOG). Finally, we use Chi-square distance to measure the similarity. The proposed algorithm is tested on PolyU and CASIA palmprint databases and the experimental results show that the recognition accuracy is optimal by comparing with some previous palmprint recognition methods, so as to meet real-time applications.

2 Fast Robustness Palmprint Recognition Algorithm

2.1 Fast Discrete Curvelet Transforms

E. J. Candes and D. L. Donoho [7] developed a multi-scale and multi-direction transform called curvelet transform in 2003. The image can be represented and approached with a series of curves via Curvelet transform. There are some original parameters of Curvelet transform listed in [7], which are proved to be optimal. Therefore, we use them in this paper.

More specifically, a pair of windows W(r) and V (t) is used in the first stage, which is called the "radial window" and "angular window," respectively. They can be shown as follows.

$$\sum_{j=-\infty}^{\infty} W^2\left(2^j r\right) = 1, r \in (3/4, 3/2); \qquad \sum_{l=-\infty}^{\infty} V^2\left(t-l\right) = 1, r \in (-1/2, 1/2); \tag{1}$$

Then, for each $j \geq j_0$, the frequency window U_j is defined in the Fourier domain by

$$U_j\left(r,\theta\right) = 2^{-3j/4} W\left(2^{-j} r\right) V\left(\frac{2^{\lfloor j/2 \rfloor}\theta}{2\pi}\right) \tag{2}$$

where $\lfloor j/2 \rfloor$ is the integer part of $j/2$, U_j is a polar "wedge" defined by the W and V, which is applied with scale-dependent window widths for each direction.

These digital transformations are linear and are considered as input Cartesian arrays of the form $f\left[t_1,t_2\right](0 \leq t_1,t_2 < n)$, and a collection of coefficients $c^D\left(j,l,k\right)$ as output can be obtained by the digital simulation in the following.

$$c^D\left(j,l,k\right) = \sum_{0 \leq t_1,t_2 \prec n} f\left[t_1,t_2\right]\overline{\varphi^D_{j,l,k}\left[t_1,t_2\right]} \tag{3}$$

where each $\varphi^D_{j,l,k}$ is a digital curvelet waveform and D stands for "digital".

2.2 Fast Robustness Palmprint Recognition Algorithm

2.2.1 Local Histogram of Oriented Gradient

In order to have a better description on the orientation the palmprint, we use the local histogram of oriented gradient (LHOG) [9] to extract the feature of orientation from each layer image obtained by using Curvelet transform.

We first obtain an orientation map of palmprint image by utilizing the gradient operator, which can be computed by

$$f_x = I * W \qquad f_y = I * W^T \tag{4}$$

$$Mag(i,j) = \sqrt{f_x^2(i,j) + f_y^2(i,j)} \qquad Ang(i,j) = \tan^{-1}\left(\frac{f_y(i,j)}{f_x(i,j)}\right) \tag{5}$$

Where I stands for original image with the size of $M \times M$, '*' is the operator of convolution, W=[-1,0,1] is a mask of convolution, $Mag(i,j)$ and $Ang(i,j)$ are gradient magnitude and angle of $I(i,j)$, $-\pi/2 < Ang(i,j) < \pi/2$. Here, Ang is considered as the orientation map of I.

Then, LHOG is formed by utilizing Ang, each pixel added to the histogram is weighted by using $Mag(i,j)$, and N stands for the orientation number utilized to cover the 360 degree range of orientation. Hence, the LHOG is obtained as follows

$$F_k = F_k + Mag(i,j) \quad \text{if} \quad (k-1)\times(2\pi/N) < Ang(i,j) < k\times(2\pi/N) \tag{6}$$

where $k = 1,2,\ldots\ldots N$, F_k represents the value corresponding to each orientation number of LHOG. Therefore, the feature of LHOG is shown as

$$LHOG = (F_1, F_2, \cdots\cdots F_N) \tag{7}$$

In order to improve the robustness for illumination and noise, LHOG is usually normalized as $LHOG = LHOG / \sum_{k=1}^{N} F_k$. Fig.1 shows the example of LHOG.

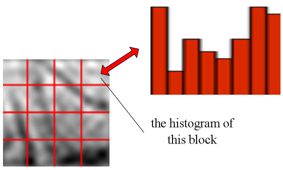

Fig. 1. The histogram of one block of LHOG

According to the principle of Curvelet transform, a palmprint ROI image with a size of 128*128 can be divided into four layers containing the texture and structure information, namely, coarse layer, detail1 layer, detail2 layer and fine layer. The structure information is distributed on the coarse layer. Detail1 and detail2 layers have part structure information, while the fine layer is usually removed because it has a lot of noises.

Next, we divide each layer image into non-overlapped blocks of equal size to reduce the interference of translation and improve the distinguish ability of extracted features. And then LHOG is extracted from each block. So we can obtain $(128\times128)/(s\times s)$ blocks from each image. The final LHOG can be defined as follows.

$$LHOG = \left(LHOG_{block1}, LHOG_{block2}, \cdots\cdots LHOG_{(128\times128)/(s\times s)}\right) \tag{8}$$

The flow chart of the proposed algorithm is as shown in the Fig.2.

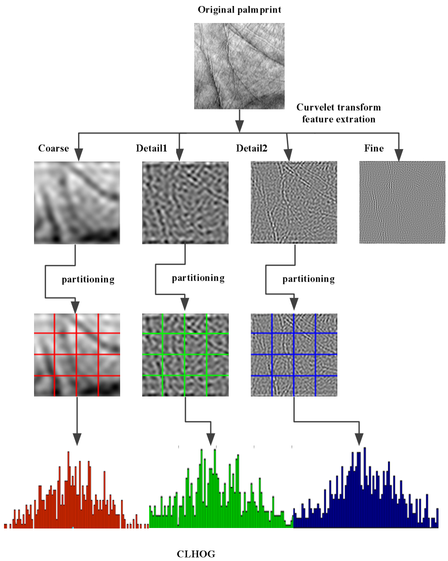

Fig. 2. The flow chart of the proposed algorithm

3 Experimental Results and Analysis

3.1 PolyU and CASIA Palmprint Database

The PolyU palmprint database contains 7752 palmprint images, which is captured from 386 different palms, and CASIA palmprint database contains 5,502 palmprint images captured from 312 subjects. For each subject, CASIA database collects palmprint images from both left and right palms. In our paper, we randomly select 900 samples (150 people, everyone has 6 samples, where one image is considered as the train image, the others are test images) from each database to test the performance of the proposed method.

The ROI (Region of Interest) image is cropped from the original palmprint image by using the method of [10]. Some examples are showed in Fig 3 and each of them contains 128×128 pixels with 256 gray levels per pixel.

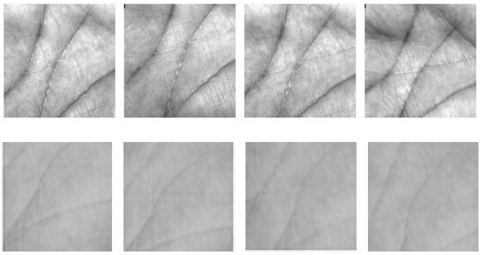

Fig. 3. Some examples of palmprint ROI images in the PolyU (top line) and CASIA (bottom line)

3.2 Identification

In this section, we carry out a series of experiments in order to show the performance of the proposed method on two palmprint databases, PolyU and CASIA palmprint databases. The genuine recognition rate (GRR) is used as an evaluation index. Each of the test images is matched with all of training images in the database. If the test palmprint image and the training image are from the same palm, the matching is considered as a correct matching, vice versa. Particularly, in order to prove the superiority of the proposed approach comparing with the traditional high-performance methods, there are four experiments are performed in the following stage.

Experiment 1: We make a comparison with the pattern of different fusion in order to obtain the optimal one. The result of Table.1 shows that the GRR of the former three layers images of the two databases is the best. So we just use the former three layers images to complete the next experiments.

Table 1. The recognition result under the pattern of different fusion for the different layers

Different layer selection	GRR%(PolyU)	GRR%(CASIA)
Coarse	87.00%	83.56%
Coarse+Detail1	98.67%	93.67%
Coarse+Detail1+Detail2	99.22%	97.33%
Coarse+Detail1+Detail2+Fine	80.53%	76.11%

Experiment 2: The aim of this experiment is to choose the optimal orientation. The block size ($s*s$) and the divided orientation number (N) have an enormous impact on the proposed method. Here, the blocks with different sizes ($4*4$, $8*8$, $16*16$, $32*32$) and different orientation numbers (N=4,6,8,9,10,12) are used to perform some experiments in order to obtain the optimal parameters for the two palmprint databases. When experiments are performed, we respectively fix the block size and

orientation number to compare the GRR. As is shown in Fig.4, when the block size is 16*16 and the orientation number is 12, the GRR of two palmprint databases achieves the highest value.

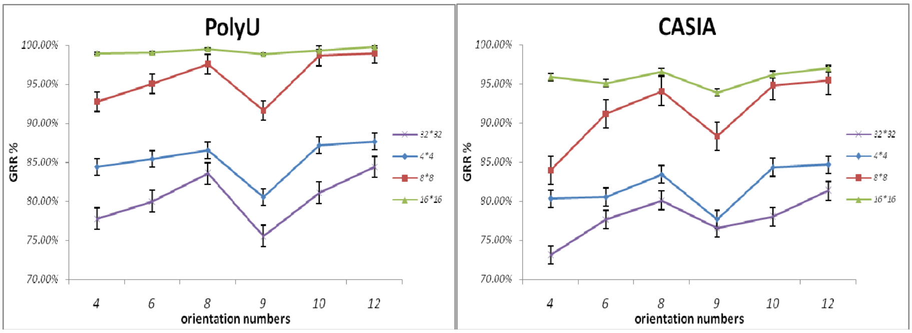

Fig. 4. the GRR of different size and orientation numbers on two palmprint databases

Experiment 3: This experiment is to compare our algorithm with some existing researches which have a good description of direction, scale and texture, such as Gabor transform [11], Curvelet, LBP [12] and LGBP [13]. Fig.5 depicts the chart of comparative result. The GRR of proposed algorithm is higher than the existing research. Distinguished information of scale is obtained by Curvelet, and the main direction characteristics are obtained via LHOG. Through verification test in two palmprint databases, the proposed algorithm has not only lower dimension, but also robustness to the rotation, translation, and illumination of palmprint.

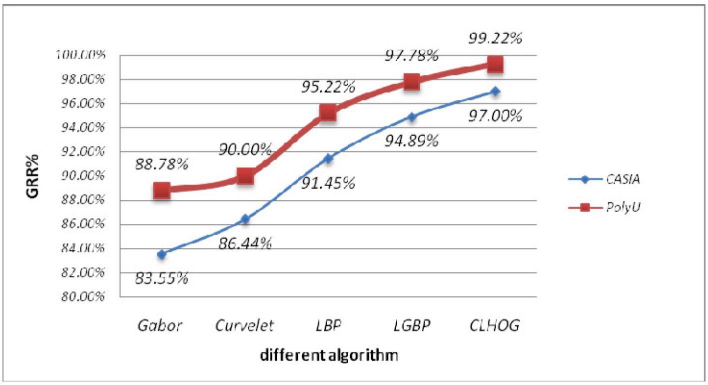

Fig. 5. The chart of comparative result

Experiment 4: On the basic of Experiment 3, this experiment compares the real-time of the algorithm mentioned above. The experiments for the proposed approach are conducted on a personal computer with the Pentium CPU 2.70 GHz and 4G RAM configured with Microsoft Windows 7 and Matlab2009a with image processing toolbox. The execution time for feature extraction, matching and total are listed in

Table 2. We can see that the total time of our algorithm on PolyU and CASIA database are 63.1369ms and 65.1112ms respectively, which is fast enough to meet the real-time requirement.

Table 2. The execution times for feature extraction, matching and total of different algorithm

Algorithm	Feature extraction/ms	Matching/ms	Total/ms
Gabor	84.3121	2.1008	86.4129
LBP	51.1285	28.5037	79.6322
LGBP	214.3269	15.3778	229.7047
CLHOG(CASIA)	43.5787	21.5325	65.1112
CLHOG(PolyU)	42.1843	20.9526	63.1369

4 Conclusions

In this paper, we proposed a CLHOG algorithm for palmprint recognition. LHOG could extract the direction features from palmprint, which were robustness for the rotation, translation, and illumination. The different scale features obtained by Curvelet could improve the recognition accuracy to larger extent. The experimental results on both PolyU and CASIA palmprint databases demonstrated the effectiveness and superiority of the proposed algorithm. By comparing with the previous high-performance palmprint recognition methods, the proposed algorithm had desirable recognition accuracy and a faster recognition rate. In the future, we will continue to improve the proposed approach, making it possible to use in some larger databases and other biometric applications.

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