A New Palmprint Identification Algorithm Based on Gabor Filter and Moment Invariant

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***Abstract*—This paper presents an effective algorithm of palmprint feature extraction. This algorithm is constructed on the basis of Gabor filter and moment invariant (MI). The process of implementing the algorithm is as follows: first, we perform wavelet transform of the original region of interest (ROI) of the palmprint image to get the approximation image (AIROI). Later, we exploit the Gabor filter to capture the texture information of the AIROI, and then compute each pixel's magnitude of the transformed image to produce a Gabor Magnitude Picture (GMP). We compute the MIs of the GMP and use the MIs as features of palmprint identification. Our experiment on an open database downloaded from PolyU Biometrics Research Center obtains very high right recognition rate.**

***Keywords*—Biometrics; Palmprint Identification; Feature Extraction; Low-Resolution; Wavelet; Gabor; Moment Invariant**

I. INTRODUCTION

Palmprint identification, which means using the prints of human palms to perform personal recognition, is a new technology of biometrics. Compared with other biometrics technologies, palmprint identification has his own advantages: stable line features, low risk of imitation, and high acceptance of users. Moreover, palmprint can be extracted from low-resolution image [1]. It can replace some previous recognition technologies such as fingerprint, iris and retina to perform personal recognition.

Feature extraction is a very important part in a biometrics security system and has great influence on the recognition result. Recently, researchers have proposed many kinds of palmprint feature extraction methods, such as line feature-based [2, 3], point feature-based [4], statistics-based [5] and wavelet transform-based [6] method. Among these methods, the statistics-based methods draw considerable attention over time, for this kind of method can extract and record features more easily.

Although there are a number of feature extraction methods, only a few of them focused on low-resolution palmprint images. In [7], Kong et. al. used a 2D Gabor filter to obtain the texture information of low-resolution palmprint images. They applied the 3 levels of Gabor filters to test low-resolution image database. However, this method mainly aimed to normal palmprint images, and the right recognition rate was not very high.

Michael KO Goh et. al. presented a new fast palmprint verification system [8]. They used a Gaussian lowpass filter to enhance image contrast and smooth texture of the original palmprint region of interest (ROI). And then they decomposed the ROI using a two-level wavelet transform. Indeed, this method in [8] was an improvement of competitive palm code scheme, and the recognition result can reach 96.7%.

In this paper, we will present a new algorithm using low-resolution palmprint images. The algorithm combines wavelet transform, Gabor Magnitude Picture (GMP) and moment invariant together to extract palmprint features. Firstly, the wavelet transform (WT) decomposes the palmprint images. It can not only reduce the size of the image, but also preserve most portion of image energy that contains major palmprint information. Additionally, 2D Gabor filters are applied to extract texture information of palmprint. The texture information is very helpful for distinguishing different palms with similar principal lines. At last, moment invariant (MI) is used to extract palmprint features. This is useful for decreasing the influence of translation and rotation of palms generated during the acquirement process of palmprint images.

II. PALMPRINT IMAGE PREPROCESSING

Palmprint image preprocessing includes two steps: palmprint ROI segmentation and acquirement of the approximate image ROI (AIROI). For the first step, please see [7]. Here we only discuss how to obtain the AIROI of a palmprint image.

As mentioned before, the AIROI is derived from the wavelet transform (WT). We utilize WT to decompose the original ROI into different frequency components, and then extract the approximate palmprint image with the size of 67×67 pixels. Because the vertical, horizontal and diagonal coefficients are associated with non-significant features of palmprint, we preserve and exploit the approximate image obtained by WT, which is the so-called AIROI. Fig. 1 shows the ROI and its AIROI.

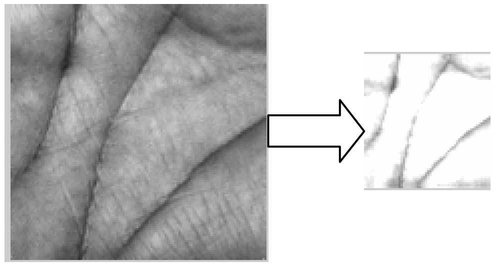


Figure 1. A ROI and its AIROI of a palmprint image

III. PALMPRINT FEATURE EXTRACTION

In order to get palmprint features, we feed the AIROI to a 2D Gabor filter, and then compute magnitude of each pixel of the filtered AIROI. We call this magnitude picture Gabor Magnitude Picture (GMP). Afterwards, we divide the GMP into some sub-GMPs that do not overlap each other. At last, we extract all the sub-GMPs' MI, and arrange them one by one to form a feature matrix. Figure 2 presents the flowchart of this feature extraction process.

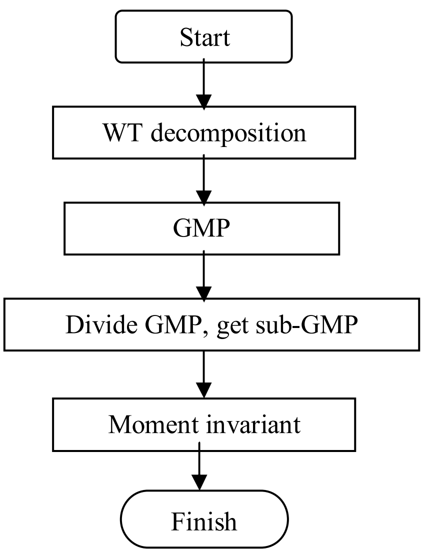


Figure 2. Flowchart of the palmprint feature extraction process

A. *Gabor Magnitude Picture*

The principal lines are the most valuable palmprint features, but we can not depend on them completely to perform personal authentication due to possible similarity among different human palms. Indeed, wrinkles also act an important role in representing palmprint. A 2D Gabor filter is used to extract texture information of palmprint. It can be viewed as a sinusoidal plane modulated by a Gaussian envelope. A 2D Gabor filter is defined as follows [7, 8, 9, 10]:

$$\begin{aligned} &G_{2D}(x, y, \theta, \mu, \sigma) \\ &= \exp\left\{-\frac{x^2+y^2}{2\sigma^2}\right\}\exp\{2\pi i(\mu x\cos\theta + \mu y\sin\theta)\} \end{aligned} \quad (1)$$

where $i^2 = -1$, μ is the frequency of the sinusoidal wave, θ is the direction from x-axis, σ stands for the standard deviation of the Gaussian envelope. In this paper, we use an improved Gabor filter used in [7] to decrease the negative influence of changing brightness and image contrast:

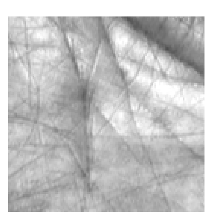
$$\begin{aligned} G'(x, y, \theta, \mu, \sigma) &= G(x, y, \theta, \mu, \sigma) \\ &- \left\{\sum_{i=-n}^{n}\sum_{j=-n}^{n}\frac{G(i, j, \theta, \mu, \sigma)}{(2n+1)^2}\right\}, \end{aligned} \quad (2)$$

where $(2n+1)^2$ is the size of the Gabor filter, and the other specific parameters are shown in Table 1.

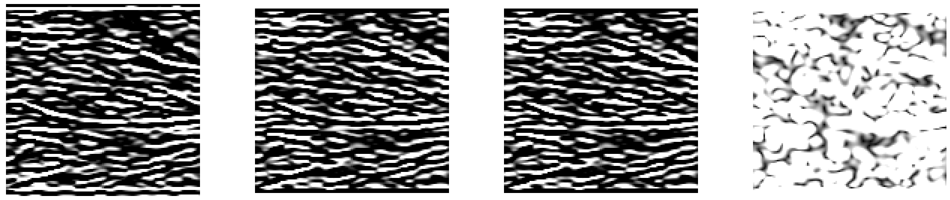
Generally speaking, Gabor magnitude feature changes much more slowly than Gabor phase feature, so a number of earlier works also exploited the magnitude rather than phase of Gabor transformation [11, 12, 13]. Here we take Gabor Magnitude Picture (GMP) as features of the palmprint image. The GMP is obtained by calculating the magnitude of each pixel point of the transformed image. Fig. 3 shows some images of the features generated from the Gabor transforms.

Table 1 Gabor filter parameters

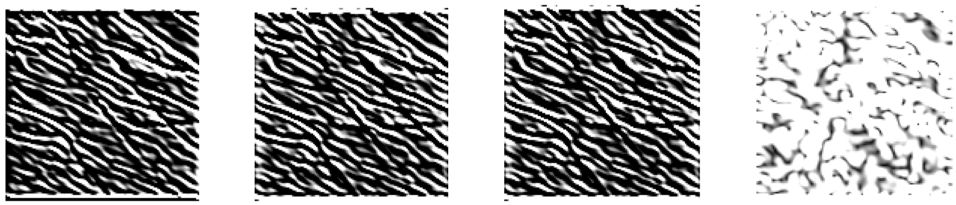
Gabor filter set	*Window size*	μ	σ	θ
1	9× 9	0.3666	1.4045	0，5π/6
2	17× 17	0.1833	2.8090	0，5π/6



(a)



(b)



(c)

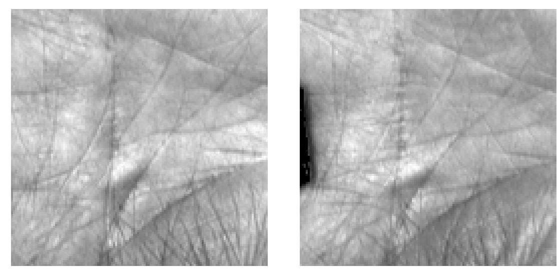
Figure 3. The original image and the generated features, (a) original image, (b)-(c) are the two sets of the features generated from two Gabor filters sets as shown in Table 1. The four images in each set are imaginary part, real part, Conventional Gabor filtered image and GMP, respectively, (b) the angle $\theta = 0$, (c) the angle $\theta = \frac{5\pi}{6}$.

B. Moment Invariant

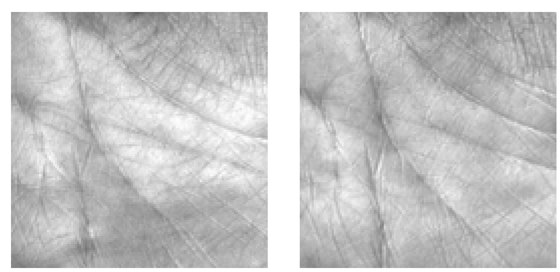
When a palmprint device captures a palmprint image, the system usually limits the location of the human palm. However, the location equipment can not fit the palm strictly. So the palmprint images are indeed acquired with tolerance of an extent of translation and rotation. Even though the ROI segmentation can provide adjustment, the adjustment is not sufficient for eliminating the influence of the translation and rotation. We utilize Hu's MI to enhance the robustness of palmprint features against rotation and translation [14, 15]. The order 1 to 7 Hu's MI can be deduced from algebraic invariants. Order 8 to 10 moment invariants are defined as in [6]. Our algorithm uses order 7 to order 10 MI.

C. Sub-Gabor Magnitude Pictur

The varying imaging condition such as varying illumination and the error of ROI segmentation have great influence on palmprint identification. Usually, the variations will appear more in some specific regions in palmprint images. Fig. 4 shows examples of palmprint ROI images obtained under varying conditions. We first divide the GMP into some non-overlapping sub-GMPs of same size. And then MI is extracted from each sub-GMP. Finally, all the sequences of MI are arranged to form a feature matrix called GMMI (Gabor Magnitude Moment Invariant). GMMI is treated as the final feature of palmprint identification.



(a)

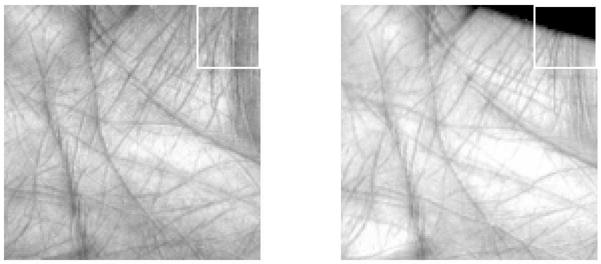


(b)

Figure 4. Examples of palmprint ROI images obtained under varying conditions. (a) the error of ROI segmentation, (b) the varying illumination.

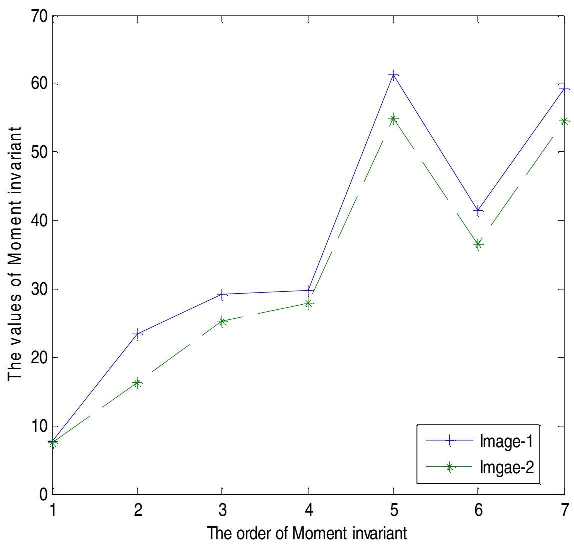
D. Robustness Analysis of the GMMI

In order to investigate the robustness of our algorithm, we compare the stability of the moment invariants obtained in three situations. The original palmprint ROI images from the same class are divided into regions of the same size of 32×32 pixels. We choose a region surroundded by a white rectangle as shown in Figure 5 to extract order 7 MI. Figure 6 shows these curves of MI we extract from two approximate images of the white regions with varying illumination and enrolling rotations. The three figures (a) to (c) of Figure 6 represent the curves extracted from ROI images, Gabor transformed images and GMP respectively. Through the results, we can see the two curves from GMP are the most similar. This indicates that our algorithm is robust to the image variations.

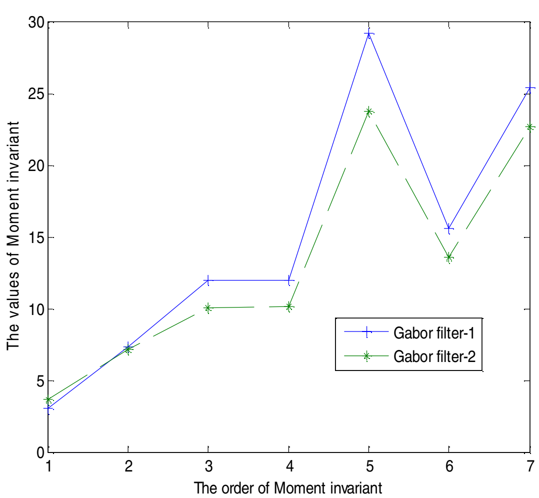


(a) (b)

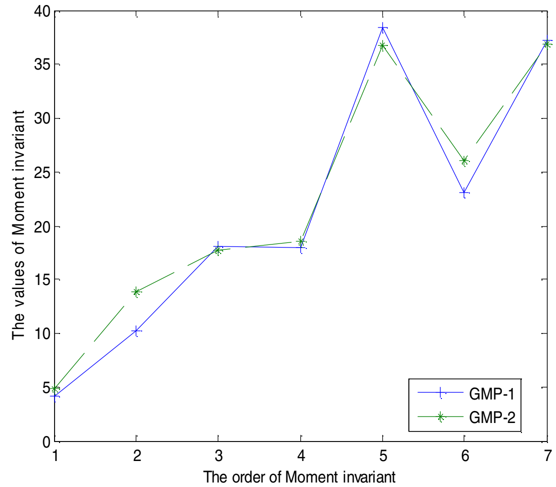
Figure 5. Two palmprint images from the same class



(a) MI extracted from ROI images directly



(b) MI extracted from Gabor transformed ROI images



(c) MI extracted from GMP

Figure 6. Robustness of different moment invariants of images with variations

IV. Palmprint Matching

For matching, the Enclidean distance (D_k) is applied to measure the similarity of the jth training sample $GMMI_j$ and the kth testing sample $GMMI_k$. Suppose we divide a GMP into $m \times m$ sub-GMPs, the MI of the pth sub-GMP of the kth testing sample is $I_{kp} = (S_{k,p,1}, S_{k,p,2}, \cdots, S_{k,p,i}), (p = 1, \cdots, n \times m \times m)$, then i is the order of the MI, and its maximum is 10. n means how many angles that are selected in Gabor transform. The distance (D_k) is defined as followed:

$$D_k = \frac{1}{n \times m \times m} \sqrt{\sum_{p=1}^{n \times m \times m} (I_{kp} - I_{jp})^2}, \qquad (3)$$

where p means how many sub-GMPs there are. The minimum of D_k indicates the maximal similarity of the training sample and the testing sample. If the D_k is minimum and the kth testing sample and the jth training sample are from the same class, the recognition is correct.

V. Experimental Results

All the experiments in this paper are performed in the computational environment of PC3.00GHz, random access memory 2.00GB, and operating system Windows XP. The program is designed and run by matlab7.0. The palmprint database downloaded from PolyU Biometrics Research Center consists of 600 palm images of 100 different palms. The palmprint image in the database is 384×284 pixels with 256 gray scales. The ROI is 128×128 pixels, and the AIROI is resized to 67×67 pixels. The first experiment is conducted as follows: two AIROIs randomly selected from six AIROI images of the same palm were used as training images; the remaining four AIROIs are used for testing. Then the GMMI of the training sample is the average of the two training images' GMMI. The GMMI of the testing sample is the average of four testing images'. All the GMPs are divided to sixteen sub-GMPs (m=4). Table 2 shows the experimental results and we can see that set 2 is better than set 1.

Table 2 The results of two sets of Gabor filters

The order of MI	*Gabor filter set*	*Recognition Rate*
7	1	97
	2	100
8	1	98
	2	99
9	1	98
	2	100
10	1	98
	2	100

With the second experiment, we test the effectiveness of the combination of GMP and moment invariant (MI). First, we apply the MI alone to test low-resolution images database, and then Gabor transform is directly used. That is, the result of the Gabor transform rather than the GMP presented is used in this experiment. In this series of trials, we also divide the feature images into sub-images as in section 3.3. The result of the second experiment is shown in Table 3. This table indicates that MI is workable for palmprint identification, but it needs a cooperation to enhance the accuracy of recognition.

In the third experiment, we compare our algorithm with the improved competitive code proposed in [8] by using the same palmprint database. In [8], they use a two-level WT to decompose original palmprint ROI images, and here we also test the effectiveness of our approach for a two-level WT. Table 4 shows the experimental result. This result shows that our algorithm is efficient and also effective to low-resolution palmprint images derived from the level 2 WT. Pay attentation that, the feature extraction time is the total time of all the palmprint images.

Table 3 Comparative results with methods. MI (9) is the abbreviation of order 9 moment invariant

Method	*Classifier*	*m*	*Recognition Rate*	*Feature matrix size*
MI (9) ′	Euclidean	4	95	16× 9
Conventional Gabor tranform+MI (9) ′	Euclidean	4	85	32× 9

Table 4 Experimental results of our algorithm and the algorithm of [9]

Method	*Feature extraction*	*Classifier*	*Wavelet level*	*The recognition Rate*	*Feature matrix size*	*Feature extraction time(sec.)*
Algorithm of [9]	Competitive index	Enclidean	1	87	67×67	28.625000
			2	85	37×37	10.562000
Our algorithm	Moment invariant	Enclidean	1	100	32× 9	18.406000
			2	99	32× 9	11.344000

VI. CONCLUSIONS

This paper presents a novel palmprint identification algorithm using low-resolution images. The rationale of the algorithm is as follows. First, since the wavelet decomposition reduces the image size, the proposed algorithm has an acceptable computational complexity. The obtained AIROI image also preserves the important palmprint information. Second, the GMP calculation procedure of our algorithm can effectively capture the texture information of the palmprint image. The GMP calculation procedure plays an important role in enhancing the representation power of the spatial texture. Thus, even though the approximate palmprint images are of low resolution, the palmprint features are discriminative. Finally, sub-GMPs is also very helpful for our algorithm to match two palms accurately.

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