Multi-scale Palmprint Recognition Using Registration Information and 2D Gabor Feature*

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Abstract. This paper describes a novel method for palmprint recognition based on registration information and 2D Gabor features. After preprocessing, a unified coordinate system is constructed for each palmprint image and used to guide ROI extraction. A multi-scale matching strategy is employed to match registration information and 2D Gabor features. In the first two levels, registration information is extracted and used to measure the global similarity between two palmprint patterns. In the third level, two palmprints are aligned with their registration information and then are matched using their corresponding Gabor features. The experimental results demonstrate the effectiveness of the method.

1 Introduction

In information and vastly interconnected society, biometric technologies have been paid more attention in personal authentication since they are more convenient, reliable and stable. Different techniques have been developed and applied in many fields. From all these techniques, palmprint is considered as a relatively new biometric feature for personal verification and have several advantages: stability and uniqueness; medium cost as it only needs a platform and a low/medium resolution CCD camera or scanner; it is very difficult to be mimicked; high user acceptance. It is for these reasons that palmprint recognition has attracted more interests from researchers.

There are many features in a palmprint image that can be extracted for authentication. Principal lines, wrinkles, ridges, minutiae points, singular points, and textures are regarded as useful features for palmprint pattern representation[1]. For palmprint, though, there is no universal method of feature extraction and recognition. In existing research, the majority focused on: points and lines[2][3][4][5]; texture analysis[6][7][8]; statistic features[9][10] and hybrid of different types of features[11].

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In this paper we investigate a novel palmprint recognition method which uses multi-scale verification strategy based on registration information and 2D Gabor features. In Level-1 stage we register two ROI images and extract their registration information using Fourier-Mellin Transformation (FMT) and phase correlation technique. In Level-2 stage, each ROI image is divided into 2×2 blocks and each pair of corresponding blocks is registered to obtain more detailed registration information. Registration information describes global similarity between two palmprint patterns at coarse level. In Level-3 stage each pair of blocks is firstly aligned with their registration information previously extracted, then a Gabor feature based image matching is performed in the superposition area of two blocks at fine level for the final confirmation. Our method is focusing on palmprint verification and is different with the method proposed in [12], which adopted multiple features and matching criteria and mainly used for palmprint identification in a large database.

The rest of this paper is organized as follows. In the Section 2 is the preprocessing stage. Section 3 presents palmprint registration with FMT and Section 4 is devoted to multi-scale palmprint verification strategy. Experimental results are listed in Section 5. At last, we discuss our algorithm and future work in Section 6.

2 Preprocessing

Our work is carried on the PolyU Palmprint Database[13]. The images of this database contain the whole palmprint and other parts of a palm and background. Therefore a preprocessing step is needed to extract the ROI. The detailed information about preprocessing steps can be referred [14]. Fig.1 shows these steps and ROI image after preprocessing.

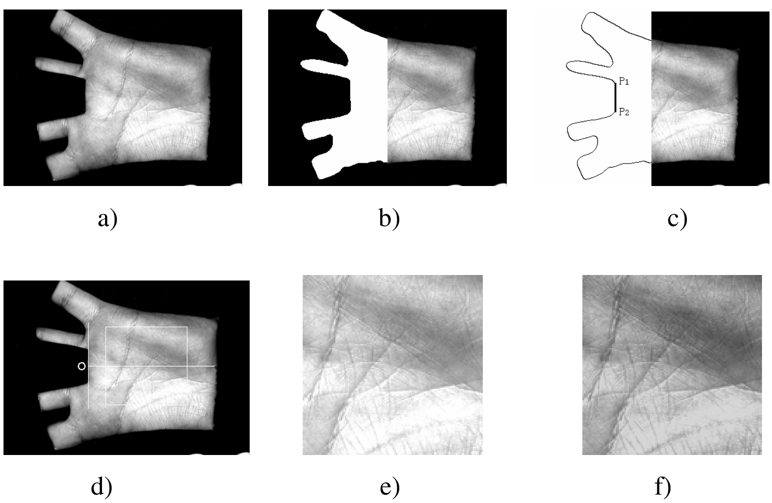


Fig. 1. The main steps of preprocessing. (a)Original database image, (b)Binarizing half of image, (c)Tracking boundary and searching line segment, (d)Building coordinate system, (e)Extracting ROI, (f)Normalizing ROI.

3 Palmprint Registration Using FMT

The Fourier-Mellin Transformation is a useful mathematical tool for the recognition of images because its resulting spectrum is invariant in rotation, translation and scale. The Fourier Transformation itself is invariant in translation in Cartesian coordinate system and in rotation by converting the Cartesian coordinate system to Polar coordinate system; the Mellin Transformation provides the invariant results for scales[15].

Here we use FMT for automatic image registration. We make a hypothesis that one palmprint image is a translated, rotated and scaled replica of another one with translation (T_x, T_y), rotation θ and uniform scale factor σ. From this point of view, the amounts of translation, rotation, and scale in constant time irrespective of the type of images can be computed by phase correlation technique based on their FMT features. Fig. 2 shows a registration example of genuine match and imposter match. The second row of the images in Fig.2 is FMT spectra derived by the FFT of the Log-Polar transformation.

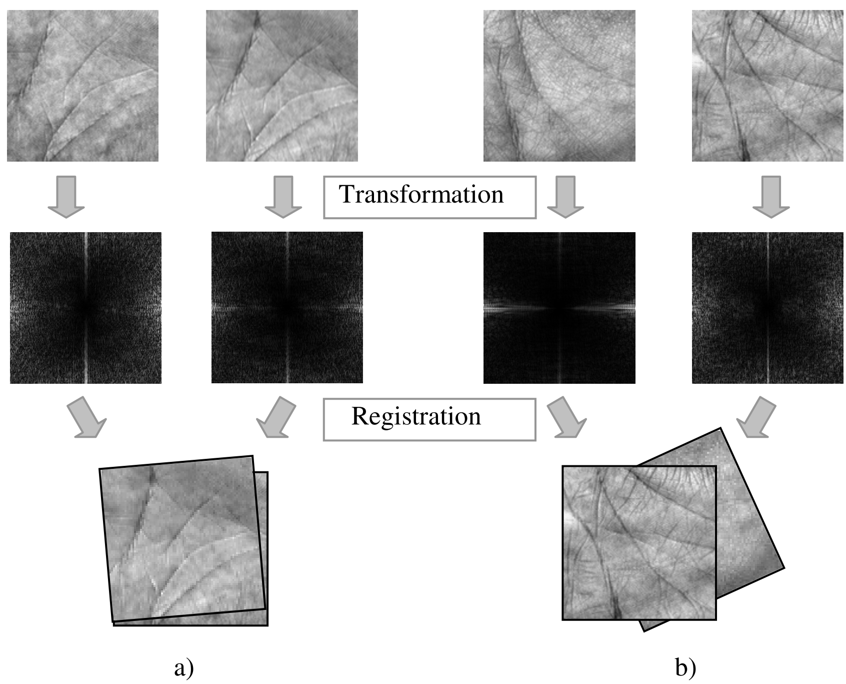


Fig. 2. Example of palmprint registration. a) Genuine registration, b) Imposter registration

4 Multi-scale Palmprint Recognition

In complex classification tasks it is widely used the approach which adopts multi-scale or hierarchical matching strategy in order to find the right trade-off between accuracy and speed. Specifically for palmprint recognition, we study a system where two palmprint images are firstly classified by a 2-scale classifier based on FMT features. Only patterns not rejected by the 2-scale classifier are forwarded to a fine classifier based on 2D Gabor features. This method combines multi-scale features and multi-stage verification strategy and it is possible to reach the trade-off between error and response time.

4.1 Level-1 Stage

Firstly, each ROI image is transformed to frequency domain by using FMT as described above. Before being mapped to log-polar plane, the FMT spectra need to be multiplied with a highpass filter to reduce the effect of discretization and logarithm resampling. Secondly, we use FMT-based registration technique to obtain the translation, rotation and scaling information of each pair of images. The vector that describes the similarity of two images is given by

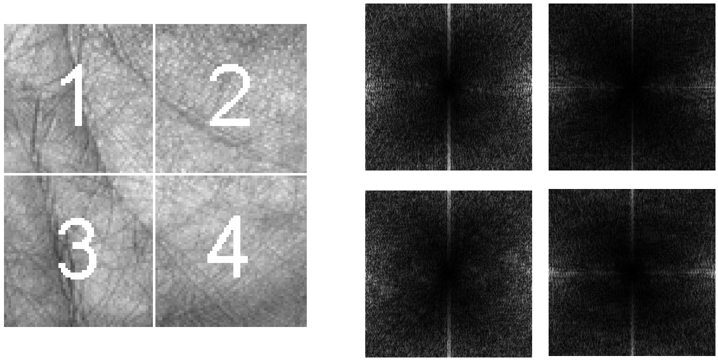
$$V_{level-1} = (d, \theta, \sigma) \tag{1}$$

where $d, \theta (0^\circ \le \theta \le 180^\circ)$ and σ are the translation distance and rotation angle and scaling factor respectively. Ideally the values of d and θ are near to zero, and the values of σ are near to 1. In realistic situation where displacements exist in acquisition, the probability that the value of d and θ is zero is very small when genuine match, because even two images captured in the same session will have a amount of offsets in translation, rotation and scale. However the amount of registration parameters when imposter match is much larger than the one when genuine match.

The main purpose of this paper is to investigate the effectiveness of multi-scale features and multi-stage verification strategy, therefore, we just define a simple linear similarity function $S_1(V_{level-1})$ to test classification performance of registration information. This function is given by

$$S_1(d,\theta,\sigma) = \alpha \exp(-\sqrt{(\frac{d-d_{\max}}{u_d})^2}) + \beta \exp(-\sqrt{(\frac{\theta-\theta_{\max}}{u_\theta})^2}) + \gamma \exp(-\sqrt{(\frac{\sigma-\sigma_{\max}}{u_\sigma})^2}) \tag{2}$$

where α, β and γ are the weight factor and $\alpha + \beta + \gamma = 1$. α, β and γ are the experiential values and their values are set in terms of the discriminability of d, θ and σ, respectively. $d_{\max}$, $\theta_{\max}$, $\sigma_{\max}$, u_d, u_θ and u_σ will be found out in training stage in terms of the sample distribution of d, θ and σ ,respectively, see in Section 5.2. $S_1(V_{level-1})$ will give the similarity score which is between 0 and 1. If this score is smaller than a threshold τ_1, 2 ROI images are verified as imposter match, otherwise, 2 images will be matched in Level-2 stage.



a) b)

Fig. 3. a) Divided ROI, b) FMT feature images of blocks.

4.2 Level-2 Stage

In this stage, ROI images are divided equally into 2×2 blocks and extracted their FMT features of each block if they are not rejected by Level-1 classifier, as shown in Fig.3. Each pair of corresponding block of two images is registered in a similar way described in Section 4.1. By dividing the ROI, more detailed registration information will be extracted. A feature vector is computed as

$$V_{level-2} = (d_1, d_2, d_3, d_4, \theta_1, \theta_2, \theta_3, \theta_4, \sigma_1, \sigma_2, \sigma_3, \sigma_4) \tag{3}$$

Also, a similarity function $S_2(V_{level-2})$ is employed to give the similarity score in terms of $V_{level-2}$, and a threshold τ_2 is used to make classification decision in this stage. If this score is higher than a threshold τ_2, two palmprints will be matched in Level-3 stage.

Registration information describes the global similarity between two palmprints at coarse level. Moreover, registration information can be used to register two palmprint images and we can match them at fine level after alignment, see in Section 4.3. τ_1 and τ_2 can be considered as a relaxing factor that controls the speed of recognition algorithm and the value of FAR in some specific occasions when necessary. The response time for the classifier at the first two levels can be reduced by using relatively large values for both τ_1 and τ_2.

4.3 Level-3 Stage

In order to improve the robustness of recognition algorithm, a fine verification stage was needed in Level-3 stage especially for genuine match. The circular Gabor filter is an effective tool for texture analysis and has been proved its efficiency for palmprint recognition and iris recognition[7][16]. We adopt 2D Gabor phase coding scheme for palmprint representation and hamming distance for feature matching. It's noted that we also adopt the optimized parameters used in [7].

Since the amount of vertical and horizontal translation, rotation angle and scaling factor have been obtained in previous stage, it's very convenient to align two palmprint blocks according to their registration parameters. Alignment process can counteract the displacement in acquisition to some extent and, therefore, is useful for Gabor feature matching. For two corresponding blocks of ROI images, the superposition area of two blocks and a mask which encloses the superposition area is generated after alignment. The normalized hamming distance is described as

$$D_1 = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} M(i,j) \cap (P_R(i,j) \otimes Q_R(i,j)) + M(i,j) \cap (P_I(i,j) \otimes Q_I(i,j))}{2\sum_{i=1}^{M}\sum_{j=1}^{N} M(i,j)} \tag{4}$$

where $P_R(Q_R)$, $P_I(Q_I)$,' $\otimes$ ', and ' $\cup$ 'have the same meanings as in [7]. The size of the mask is $M \times N$.

Then we compute the distance by

$$D_0 = 1 - \frac{1}{4}\sum_{i=1}^{4} D_i \tag{5}$$

Obviously D_0 is between 0 and 1. For the best matching, D_0 should be 1.

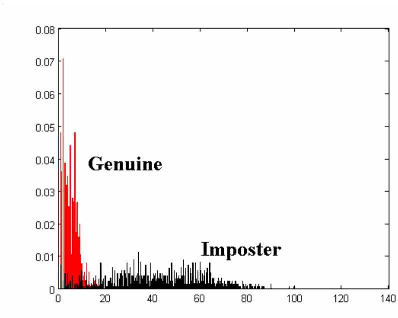
5 Experimental Results

5.1 Palmprint Image Database

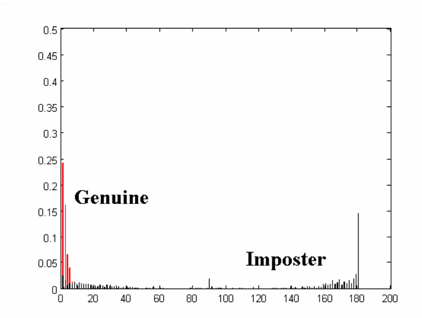
The PolyU Palmprint Database is so far the first and the largest open palmprint database, which contains 600 grayscale images corresponding to 100 different palms in BMP image format. These images were captured from above 300 different palms and each palm was captured 10 images. Factors such as population coverage and capturing time interval had been considered when constructing database. Six samples were selected from 10 images of each of these palms were collected from the same person in two sessions, where 3 samples were captured in the first session and the other 3 in the second session. The average interval between the first and the second collection was two months.

5.2 Training Stage

In our experiment, we divide the Database into 2 subsets. The first subset includes total 300 images of the first 50 palms and is used to train the parameters of $S_1(V_{level-1})$ and $S_2(V_{level-2})$, e.g. $d_{\max}$, $\theta_{\max}$, $\sigma_{\max}$, u_d, u_θ and u_σ etc. The



a)



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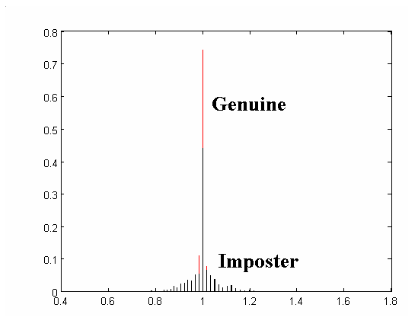


c)

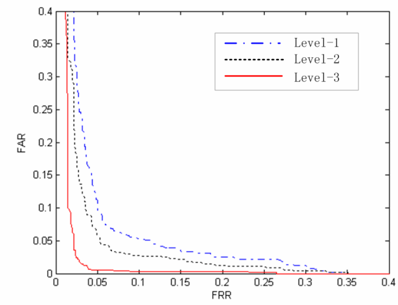
Fig. 4. Distribution of training samples. a) Distribution of d , b) Distribution of θ , c) Distribution of σ .

second one includes the rest of images and is used to test the recognition performance. The training subset and test subset were from different palms. This kind of partition can be helpful to test the generality of recognition algorithm.

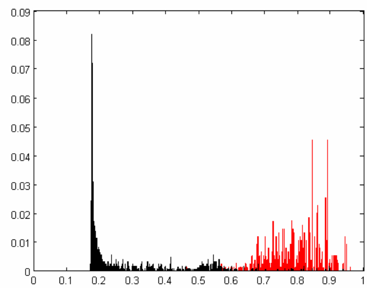
According to the distribution of training samples when genuine match, we can train the parameters of $S_1(V_{level-1})$ and $S_2(V_{level-2})$, which will be used to compute similarity score. The distribution of d , θ and σ obtained in Level-1 stage can be seen in Fig.5. As it is clearly seen, d and θ have a strong discriminability in distribution while the discriminability of σ is weaker.

5.3 Test Stage

In this stage, each sample in test subset is matched against the remaining samples of the same palm to compute the False Rejection Rate (FRR). The first sample of each palm in the test subset is matched against the first sample of the remaining palms in this subset to compute the False Acceptance Rate(FAR).



a)



b)

Fig. 5. a) Receiver operating curve for Level-1, Level-2 and Level-3 matching scheme, b) Genuine and imposter match score distributions in Level-3.

Table 1. Performance Evaluation

Matching Scheme	EER(%)
Level-1	6.83
Level-2	5.32
Level-3	2.42

To test performance of different verification levels, we carried out totally 6 verification for imposter and genuine match and for Level-1,Level-2 and Level-3,respectively. It is noted that Level-2 and Level-3 are combining classifiers. The performance of different levels on test subset is presented by Receiver Operating Characteristic (ROC) curves. Fig.5(a) illustrates the ROC curves for 3 levels and Table 1 shows the performance evaluation in terms of EER. Note that Level-3 matching scheme achieves better performance than Level-2, while Level-2 better than Level-1, the experimental results reveals the efficiency of combining levels matching scheme compared to both Level-1 and Level-2 in the verification task, this also can be seen from the Table 1. The normalized score of genuine match and imposter match in Level-3 is illustrated in Fig.5(b).

6 Clusions and Future Work

A novel method to palmprint feature matching strategy is proposed in this paper. A multi-scale verification strategy is employed to match registration information and 2D Gabor feature. Registration information is extracted to describe the global similarity and make classification at coarse level and 2D Gabor feature is extracted to verify two palmprints at fine level. The experimental results show that this strategy achieves good performance for palmprint recognition and still have potential to improve. In the future work, we will investigate the fusion of registration information with the other features. The design of compact classifier will be investigated as well.

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