Personal Recognition Based on the Gabor Features of Colour Palmprint Images

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Abstract—In this paper a personal recognition system based on the Gabor features of colour palmprint images is described. The features are extracted by a bank of Gabor filters from the palmprint region represented by three primary spectral components: R, G and B. The system, based on fusion at the matching-score level, is used to improve the recognition accuracy. The recognition results of the system are compared with the results of a grey-level-based palmprint-recognition system for the same database.

I. INTRODUCTION

A Gabor-based approach is widely used for the feature extraction in biometric applications, such as iris [1], face [2], fingerprint [3] and palmprint recognition [4], [5], [6]. Zhang et al. [5] describe an online palmprint-recognition system that is based on a 2D Gabor phase-encoding scheme for palmprint-feature extraction. By applying the tuning process to a training set consisting of grey-level palmprint images (384 × 284, 75 dpi), the optimal three parameters \( (\theta, u, \sigma) \) of a \( 35 \times 35 \) Gabor filter were selected. The verification test was made on grey-level palmprint images from 193 people, with 20 images of the left and right palms. The results of the verification showed a 98% genuine acceptance rate and a 0.04% false acceptance rate for a threshold value of 0.3425. The EER was 0.6%. The identification tests with three registration databases for \( N = 50, 100 \) and 200 users were performed. The best recognition rate was achieved for a 1-to-50 identification, where the system operated at about a 99.5% genuine acceptance rate; for a 1-to-100 identification, at a 0.1% false acceptance rate and a 97% genuine acceptance rate; and for a 1-to-200 identification, at a 0.1% false acceptance rate and a 95% genuine acceptance rate.

In [6] a bank of twelve Gabor filters was tested for verification on a database consisting of 4647 palmprint images (about 40 images from 120 people from the PolyU database [7]). The regions of interest, cropped from grey-level palmar images, were represented by two resolutions, i.e., \( 128 \times 128 \) and \( 64 \times 64 \) pixels. The test showed that three Gabor filters, size \( 35 \times 35 \), with parameters \( u = 0.0916, \sigma = 5.6179, \theta = 0, \pi/4 \) and \( 3\pi/4 \) achieved the best results for the region of interest (ROI) with size \( 128 \times 128 \): for a false acceptance rate smaller than \( 10^{-2} \), the false rejection rates were 5.6\% (for \( \theta = 0 \)), 2.9\% (for \( \theta = \pi/4 \)) and 6.4\% (for \( \theta = 3\pi/4 \)). A verification test for ROI of \( 64 \times 64 \) showed that the best filter parameters were: size \( 17 \times 17, \theta = \pi/4, u = 0.1833, \) and \( \sigma = 1.8090 \). The result was a 2.5\% false rejection rate at a smaller than \( 10^{-2} \) false acceptance rate.

Pan and Ruan proposed a novel approach to Gabor feature-based palmprint recognition, which combines a Gabor filter bank and an improved two-dimensional PCA ((2D)\( ^2 \)PCA) for dimensionality reduction [4]. The (2D)\( ^2 \)PCA reduces the dimension of the feature space in both row and column directions resulting in fewer coefficients for feature matching. The main steps involved in the system are:

1) The Gabor features of different scales and orientations are extracted (there were 30 different Gabor filters);
2) The (2D)\( ^2 \)PCA is then applied for the dimensionality reduction of the feature space in both row and column directions;
3) The Euclidian distance is used for 1-NN classification.

The database consists of 800 left-hand images from 80 people. A Gabor feature-based (2D)\( ^2 \)PCA gives the best recognition rate of 99\% when five training samples per class were used. Also, the genuine acceptance rate (GAR) is higher than the Gabor feature-based 2DPCA at the same false acceptance rate (FAR).

II. DESCRIPTION OF THE SYSTEM

The proposed system (Fig. 1) consists of six parts: acquisition unit, pre-processing, feature extraction, thresholding, matching and decision based on fusion. The colour RGB images of the right hand are scanned at 180 dpi / 256 grey levels in the acquisition unit. In the pre-processing module the following steps are performed: conversion to grey-scale image, binarization of the grey-scale image with thresholding, border following of the contour of the hand, detection of the stable points, rotation of the hand in the normal position and finally, a determination of the region of interest (ROI). After that, the ROIs are cropped separately from the colour-palmprint image R, G, B and resized to \( 64 \times 64 \) pixels. The primary spectral components R, G and B of each ROI are processed independently. The feature extraction is based on a 2D Gabor filter. The binarization of the features is made with a zero threshold. The palmprint matching is based on a generalised
Hamming distance. Fusion at the matching-score levels for all three primary spectral components is made.

A block-scheme of the personal recognition system based on the Gabor features for colour ROIs of palmprint images is shown in Fig. 1.

B. Pre-processing

In the first step of pre-processing a palmprint image is extracted from the background. For that we use a grey-scale image whose values of image intensities are obtained as

\[ I = \frac{r + g + b}{3} \]

where \( r, g \) and \( b \) are the R, G and B primary spectral values. The obtained image has grey intensities set in the interval from 0 to 255 (8 bits). Because of the good impose of the lightning conditions during the image acquisition in the segmentation of the grey-scale image, simple global thresholding is used. With the use of the border-following algorithm [8] in the binary image, the contour of the hand is obtained. On the contour of the hand the stable points are searched for, which will then be used as reference points for determining the region of interest (ROI). Previous research [5], [9] has determined determined that these are the points \( (T_1 \text{ and } T_2) \) that lie on the tangent of the gaps between the ring finger and the little finger and between the index finger and the middle finger (see Fig. 3(a)). The connecting of the points \( T_1 \) and \( T_2 \) will be used for determining the image ROI and for the geometric normalization of the palmprint image. The geometric normalization is carried out by rotating the palmprint image so that a line connecting \( T_1 \) and \( T_2 \) has the angle 0° with the \( x \) coordinate axis of the image. The coordinates of the ROI that are obtained on the grey-scale image are used for cropping the ROI on primary spectral images (R, G, B) to acquire ROIs for the R, G and B image. The position of the ROI is defined by a \( d \times d \) square that is moved \( d/10 \) pixels below the line that connects the stable points \( T_1 \) and \( T_2 \) (Fig. 3(b)). In such a way the determined ROI is cropped from the corresponding colour images of the palm (R, G and B). After that, all the regions (in images R, G and B) are resized to 64 × 64 pixels with the use of bicubic interpolation (Fig. 3(c)).

The above-described procedure is used for modeling two experimental databases that are composed of 64 × 64 pixel ROIs. The first database Database \( B_1 \) contains 648 ROIs from 81 people (eight ROIs per person). The second database Database \( B_2 \) contains 787 ROIs of the right palm of 80 people (about 10 ROIs per person).

A. Acquisition

Colour RGB images of the right hand are scanned at 180 dots per inch (dpi) / 256 levels. The user puts his/her hand on the scanner surface with the fingers spread naturally; there are no pegs or any other hand-position constrainers. An example of an image acquired with this method is shown in Fig. 2.

![Acquired palmprint image](image)

Fig. 2: Acquired palmprint image
C. Feature extraction based on a 2D-Gabor filter

Palmprint authentication is usually based on texture analysis. Gabor filters and Gabor filter banks are widely applied for feature extraction from texture images [5], [6]. A circular Gabor filter, in general, has the following form:

\[ G(x, y, \theta, u, \sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} e^{2\pi i (ux \cos \theta + uy \sin \theta)} \]

where \( i = \sqrt{-1} \), \( u \) is the frequency of the sinusoidal wave; \( \theta \) controls the orientation of the function and \( \sigma \) is the standard deviation of the Gaussian envelope. The \( \sigma \) and \( u \) are dependent on the size of the filter with \( \sigma \cdot u = \text{const} \). To make it more robust against brightness, a discrete Gabor filter, \( G[x, y, \theta, u, \sigma] \), is produced and the filter values are grouped around zero, so that the average filter value is 0, while the obtained filter is called the zero DC Gabor filter \( \tilde{G} \):

\[ \tilde{G}[x, y, \theta, u, \sigma] = G[x, y, \theta, u, \sigma] - \frac{\sum_{n=-\infty}^{\infty} \sum_{j=-\infty}^{\infty} G[i,j,\theta,u,\sigma]}{(2n+1)^2}, \]

where \( 2n + 1 \) is the filter size.

Convolution in the spatial domain of each primary spectral ROI with the selected Gabor filter \( \tilde{G} \) is performed. For each primary colour ROI image the convolution gives the real part of the texture image and the imaginary part of the texture image.

The real and imaginary parts of the texture image are binarized using a zero threshold. The binary pixel value of the real part \( b_r \) or of the imaginary part \( b_i \) of the filtered image is obtained as follows:

\[ b_r = 1, \quad \text{Re}[\tilde{G}[x, y, \theta, u, \sigma] * I] \geq 0 \]
\[ b_r = 0, \quad \text{Re}[\tilde{G}[x, y, \theta, u, \sigma] * I] < 0 \]

for the real part of the filtered texture image \( P_R \), and

\[ b_i = 1, \quad \text{Im}[\tilde{G}[x, y, \theta, u, \sigma] * I] \geq 0 \]
\[ b_i = 0, \quad \text{Im}[\tilde{G}[x, y, \theta, u, \sigma] * I] < 0 \]

for the imaginary part of the filtered texture image \( P_I \), where ‘*’ denotes the 2D convolution in the spatial domain and \( I \in \{I^R, I^G, I^B\} \) is the primary spectral ROI image. An example of the appearance of the real and imaginary textures obtained for a red colour ROI palmprint image is given in Fig. 4.

D. Feature matching

Let \( \{P_1, ..., P_n\} \) be the live templates that will be tested and \( \{Q_1, ..., Q_m\} \) be the templates from the database, where \( n \) is the number of live templates and \( m \) is the number of templates in the database, \( n > m \). For the matching the generalised Hamming distance is utilized. It is carried out from the normal Hamming distance, which has the form

\[ D_0(P, Q) = \frac{1}{2N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} (P_R(i, j) \otimes Q_R(i, j) + P_I(i, j) \otimes Q_I(i, j)) \]

where \( N \) is the size of the filtered image, \( P_R \) and \( P_I \) are the real part and the imaginary part of the live template \( P \), and \( Q_R \) and \( Q_I \) are the real part and the imaginary part of the database template \( Q \), respectively, and \( \otimes \) is the exclusive OR operator. In order to provide translation invariance matching in both directions, the generalised Hamming distance is used

\[ D_{min}(P, Q) = \min_{|s|<S,|t|<T} \frac{1}{2H(s)H(t)} \sum_{i=max(1,1+s)}^{\min(N,N+s)} \sum_{j=max(1,1+t)}^{\min(N,N+t)} (P_R(i+s, j+t) \otimes Q_R(i, j) + P_I(i+s, j+t) \otimes Q_I(i, j)) \]

where the shifting parameter in the horizontal direction is \( s < S \), and in the vertical direction it is \( t < T \), where \( S = 6 \) and \( T = 6 \) are the parameters that control the range of the horizontal and vertical translations of a feature in the matching process, respectively. \( H(s) \) and \( H(t) \) are defined as

\[ H(q) = \min(N, N + q) - \max(1, 1 + q) + 1 \]

where \( q \) is \( s \) or \( t \).

E. Fusion at the matching-score level

Fusion is based on the total similarity measure (TSM) that is obtained as a weighted sum of the similarity measures \( S_R, S_G \) and \( S_B \):

\[ TSM(P_k, Q_l) = w_R \cdot S_R + w_G \cdot S_G + w_B \cdot S_B \]

where \( S_i = e^{-D_{min}}, i \in \{R, G, B\}, D_{min}^{P_k} \) is the minimum generalised Hamming distance for the corresponding primary spectral components, the live template is \( P_k \), the current template from the database is \( Q_l \) and \( w_R, w_G, w_B \) are the weights of the corresponding primary spectral ROI images. The weights are obtained on the basis of the first two experiments (see Experiment 1, and Experiment 2). The parameters \( w_R, w_G, w_B \) for the R, G and B primary spectral components are empirically calculated:

\[ w_i = \frac{\mu_i}{\mu_R + \mu_G + \mu_B} \]

where \( \mu_i \) is the mean recognition rate in Experiment 2 for the best filter (filter no. 10; Table II) for \( i \) primary spectral components, \( i \in \{R, G, B\}, \mu_R, \mu_G, \mu_B \) are the corresponding mean recognition rates for the same filter. The weights are found to
be \( w_R = 0.33430, w_G = 0.33305 \) and \( w_B = 0.33265 \), and \( w_R + w_G + w_B = 1 \). The classification rule is based on the maximum total similarity measure (TSM) by using the 1-NN rule.

III. EXPERIMENTS AND RESULTS

In this section, four experiments are described. The first experiment evaluates the information content of the Gabor-based features of the primary spectral components R, G and B. The second experiment selects the best filter parameters for the recognition performed on the primary spectral components R, G and B. The third experiment checks if whether fusion at the matching-score level of the primary spectral components improves the recognition accuracy. Finally, we perform an open-set identification with fusion.

Two palmprint databases are utilized for the experiments. The first database, \( B_1 \), contains 648 palmprint images of 81 people. From each person 8 images of the right palm are taken. The second database, \( B_2 \), contains 787 palmprint images of 80 people (10 images of the right palm from 71 people, 9 images from 6 people, 8 images from 2 people, and 7 palmprint images from 1 person).

A. Experiment 1

In the first experiment, Filters 5-8 from Table I are used. They are chosen according to the Gabor filters used in [6]. From the database \( B_1 \) 80 palmprint images of 10 people (8 images per person) are taken.

<table>
<thead>
<tr>
<th>Filter no</th>
<th>Sizes</th>
<th>( \theta )</th>
<th>( u )</th>
<th>( \sigma )</th>
</tr>
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<tr>
<td>1</td>
<td>( 9 \times 9 )</td>
<td>0</td>
<td>0.3666</td>
<td>1.4045</td>
</tr>
<tr>
<td>2</td>
<td>( 9 \times 9 )</td>
<td>45</td>
<td>0.3666</td>
<td>1.4045</td>
</tr>
<tr>
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<td>( 9 \times 9 )</td>
<td>90</td>
<td>0.3666</td>
<td>1.4045</td>
</tr>
<tr>
<td>4</td>
<td>( 9 \times 9 )</td>
<td>135</td>
<td>0.3666</td>
<td>1.4045</td>
</tr>
<tr>
<td>5</td>
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<td>0</td>
<td>0.2444</td>
<td>2.1067</td>
</tr>
<tr>
<td>6</td>
<td>( 13 \times 13 )</td>
<td>45</td>
<td>0.2444</td>
<td>2.1067</td>
</tr>
<tr>
<td>7</td>
<td>( 13 \times 13 )</td>
<td>90</td>
<td>0.2444</td>
<td>2.1067</td>
</tr>
<tr>
<td>8</td>
<td>( 13 \times 13 )</td>
<td>135</td>
<td>0.2444</td>
<td>2.1067</td>
</tr>
<tr>
<td>9</td>
<td>( 17 \times 17 )</td>
<td>0</td>
<td>0.1833</td>
<td>2.8090</td>
</tr>
<tr>
<td>10</td>
<td>( 17 \times 17 )</td>
<td>45</td>
<td>0.1833</td>
<td>2.8090</td>
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<td>12</td>
<td>( 17 \times 17 )</td>
<td>135</td>
<td>0.1833</td>
<td>2.8090</td>
</tr>
</tbody>
</table>

1) Experiment 1a: We want to show that the information content of each of the three primary spectral components of the same ROI image, even though they are correlated, is different. We determine the normal Hamming distances of the binary Gabor features of the primary spectral components R, G and B, taken from the same image ROIs of the same person for Filters 5-8. We take the minimum distance of these four filters. Experiment 1a is repeated for ten people from database \( B_1 \).

Fig. 5 shows the mean and the standard deviation of the normal Hamming distances for each of ten people and for the pairs RG, RB and GB. From Fig. 5 we can see that the normal Hamming distances vary, and they are the smallest for the GB pair. We can conclude that there exists a difference in the information for different primary spectral components of the same image ROIs.

In the following two experiments (1b, 1c) we want to show that the generalised Hamming distances of the image ROIs of the same person are smaller than the generalised Hamming distances of the image ROIs of different people.

2) Experiment 1b: We take 8 palmprint images from one person and compute the generalised Hamming distance for the binary Gabor features of different image ROIs of the same person. We have 28 combinations for RR, GG, BB, RG, RB, and GB. Experiment 1b was repeated for ten people from database \( B_1 \).

Fig. 6 shows the mean and the standard deviation of the generalised Hamming distances for six pairs of combinations.

3) Experiment 1c: We compute the generalised Hamming distances of the binary Gabor features of the image ROIs of
ten different people. We have 2880 image combinations for the RR, GG, BB, RG, RB and GB primary spectral components.

Fig. 7 shows the mean and the standard deviation of the generalised Hamming distances for six combinations of pairs. From Fig. 7 we can see that the generalised Hamming distances of the image ROIs from different people are greater than the generalised Hamming distances from Experiment 1a and Experiment 1b.

B. Experiment 2

The experiment selects the best filter from a bank of Gabor filters for the R, G and B primary spectral component. The parameters of the bank of Gabor filters coincide with the parameters in [6]. They are displayed in Table I. The filter sizes are $9 \times 9$, $13 \times 13$ and $17 \times 17$. The orientations $\theta$ are $0, \pi/4, \pi/2, 3\pi/4$. After the best filter is found, it will be used in the last two experiments.

For the experiment the whole database $B_1$ is used: three palmprints of a person are used for the enrolment, and the remaining images are used for testing. The experiments are repeated ten times, and in each experiment three samples for the enrolment are randomly selected.

The recognition results of the colour palmprint image, the grey image and the fusion based on the primary spectral components are given with the mean and the standard deviation for ten experiments. The recognition accuracy for the R primary spectral component is 98.51 ± 0.37, for G it is 98.29 ± 0.43, for B it is 98.37 ± 0.54, and for grey it is 98.31 ± 0.52, and finally for the fusion based on primary spectral components the best recognition accuracy is achieved, i.e., 98.71 ± 0.37.

C. Experiment 3

The goal of this experiment is to see how fusion based on primary spectral components at the matching-score level affects the result of the recognition in accordance with the grey image for the best filter.

The experiment utilizes the whole database $B_2$: three palmprints of a person are used for the enrolment, and the remaining images are used for testing. The experiment is repeated ten times, and in each experiment three samples for the enrolment are randomly selected.

The recognition results of the colour palmprint image, the grey image and the fusion based on the primary spectral components are displayed in Table II. The results of the recognition are presented with the mean and the standard deviation for 10 experiments (Table II). From Table II it can be seen that the best recognition accuracy is 99.23 ± 0.45 for the primary spectral component R, 98.86 ± 0.63 for G and 98.74 ± 0.78 for B, and this is achieved for Filter 10, size 17x17, with the parameters $\theta = \pi/4, u = 0.1833, \sigma = 2.8090$.

D. Experiment 4

This experiment will show how our personal identification system works with open-set identification. Fusion is based on the total similarity measure at the matching-score level of primary spectral component features obtained with the best filter.

For the $B_2$ database all 80 people are selected as genuine users, and from the $B_1$ database all 81 people are labelled as imposters. For 80 genuine users 3 out of about 10 palmprint images are used as templates for the extracting features to be stored in the biometric database and the other part called the test samples is used for testing the performance of the system. For 81 imposters, all 8 palmprint images are used for testing.

The detection rate (DR) and the false-alarm rate (FAR) as a function of the threshold for the open-set identification are evaluated for the following outcomes:

i) A live template of the user has the maximum TSM with respect to the database template(s), which corresponds to the same user, and this measure exceeds the threshold value. The user is correctly identified.

ii) A live template of the user has the maximum TSM with respect to the database template(s) and this value exceeds the
given threshold but these templates do not correspond to the correct user. The user is misclassified.

iii) A live template of the user has the maximum TSM with respect to the arbitrary database template, but this value measure does not exceed the threshold value. The user is incorrectly rejected as an imposter.

iv) A live template of the imposter has the maximum TSM with respect to the arbitrary database template and this measure exceeds the given threshold. In this case an imposter is incorrectly identified as a user.

v) A live template of the imposter has the maximum TSM with respect to an arbitrary database template and the measure does not exceed the threshold. An imposter is correctly rejected.

The DR and FAR depicted in Fig. 8 are evaluated as follows:

\[
DR(T) = \frac{\text{number of templates for case i)}}{\text{the total number of templates of users}}
\]

\[
FAR(T) = \frac{\text{number of templates case ii) and iv)}}{\text{the total number of templates of users and imposters}}
\]

![Fig. 8: Detection rate plotted against the False Alarm Rate](image-url)

**IV. CONCLUSION**

We have developed a colour-based palmprint personal identification system. A pre-processing algorithm extracts the central area from a palmprint image size 64x64 for feature extraction. We use 2D Gabor phase coding to represent a palmprint image using its texture feature, and apply a generalised Hamming distance for the matching measurement. We achieve a recognition accuracy of 98.71 ± 0.37 for fusion of the colour palmprint images, while the best recognition accuracy for a grey palmprint image is 98.31 ± 0.52 for the same database.

In summary, we conclude that our colour-based palmprint-identification system has achieved a slightly better performance in comparison with the grey-scale system.

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