Fusion of Multispectral Palmprint Images For Automatic Person Identification

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Abstract—Reliability and accuracy in personal identification system is a dominant concern to the security world. Biometric has gained much attention in this subject recently. Many types of personal identification systems have been developed, and palmprint identification is one of the emerging technologies. This paper presents a novel biometric technique to automatic personal identification system using multispectral palmprint technology. In this method, each of spectrum images are aligned and then used to extract palmprint features using 1D log-Gabor filter. These features are then examined for their individual and combined performances. Finally, the hamming distance is used for matching of palmprint features. The experimental results showed that the proposed method achieve an excellent identification rate and provide more security.

Index Terms—Biometrics, Identification, Multispectral palmprint, 1D log-Gabor filter, Image fusion, Score level fusion.

I. INTRODUCTION

The rapid growth in the use of many applications in different areas, such as public security, access control and surveillance, requires reliable and automatic personal identification for effective security control. Traditionally, passwords (knowledge-based security) and ID cards (token-based) have been used. However, security can be easily breached when a password is divulged or a card is stolen; further, simple passwords are easy to guess and difficult passwords may be hard to recall [1]. At present, applications of biometrics are rapidly increasing due to inconveniences in using traditional identification methods. Biometric technology may be defined as the automated use of physiological or behavioral characteristics to determine an individual’s identity [2].

Currently, a number of biometrics-based technologies have been developed and hand-based person identification is one of these technologies. This technology provides a reliable, low-cost and user-friendly viable solution for a range of access control applications [3]. In contrast to other modalities, like face and iris, hand biometry offers some advantages [4]. First, data acquisition is economical via commercial low-resolution cameras, and its processing is relatively simple. Second, hand-based access systems are very suitable for indoor and outdoor usage, and can work well in extreme weather and illumination conditions. Finally, hand features are more stable over time and are not susceptible to major changes.

Palmprint identification is one kind of hand-biometric technology and a relatively new biometrics due to its stable and unique characteristics. The rich texture information of palmprint offers one of the powerful means in personal identification. In this paper, we first propose a multispectral palmprint identification algorithm based on single spectrum. It extracts phase features from each spectrum palmprint image to process the inherent unique characteristics of the palmprint. Further, the paper presents a method for fusing information from palmprint images captured under different light spectrum [5], at both the image and feature level.

This paper is organized as follows. A scheme for multispectral palmprint identification is presented in section 2. 1D log-Gabor filter and encoding process are discussed in section 3. Palmprint matching is shown in sections 4. The fusion techniques for fusing the information presented by extracted features is presented in section 5. A sections 6 is devoted to describe evaluation criteria. The experimental results prior to fusion and after fusion are presented and commented in section 7. Finally, the conclusions and further works are presented in sections 8.

II. SYSTEM DESIGN

Fig. 1 illustrates the various modules of our proposed multispectral palmprint identification (open set) system. The proposed system consists of preprocessing, feature extraction, matching and decision stages. To enroll into the system database, the user has to provide a set of training multispectral palmprint images ⟨Blue, Green, Red and Near-IR (NIR)). Typically, a feature vector is extracted from each spectrum which describes certain characteristics of the palmprint images using 1D log-Gabor filter. Finally, the feature vectors are stored as reference templates. For identification, the same feature vectors are extracted from the test palmprint images and the maximum distance is computed using all of reference templates in the database. Based on this matching score (hamming distance), a decision about whether to accept or reject a user is made.

III. LOG-GABOR FEATURE EXTRACTION

The whole image of the palmprint (each spectrum) is not really useful. Only some characteristics are needed. Therefore, each spectrum images may have variable size and orientation. Moreover, the region of not-interest may affect accurate processing and degrade the identification performance.
Therefore, image preprocessing (Region Of Interest extraction (ROI)) is a crucial and necessary part before feature extraction. 1D log-Gabor filter is able to provide optimum conjoint representation of a signal in space and spatial frequency [6]. In our method, the features are generated from each spectrum sub-image (ROI) by filtering with 1D log-Gabor filter.

A. Log-Gabor filter overview

Gabor features are a common choice for texture analysis. They offer the best simultaneous localization of spatial and frequency information. One weakness of the Gabor filter is that the even symmetric filter will have a DC component whenever the bandwidth is larger than one octave [7]. To overcome this disadvantage, a type of Gabor filter known as log-Gabor filter, which is Gaussian on a logarithmic scale, can be used to produce zero DC components for any bandwidth. The frequency response of a log-Gabor filter is given as:

\[ G(f) = \exp \left\{ \frac{-\left(\log(f/f_0)\right)^2}{2\left(\log(\sigma/f_0)\right)^2} \right\} \]

where \( f_0 \) represents the center frequency, and \( \sigma \) gives the bandwidth of the filter. In the experiments, The parameters of log-Gabor filter were empirically selected as \( f_0 = 1/2 \) and \( \sigma = 0.0556 \), are used in all calculation.

B. Log-Gabor feature representation

We utilize the response of 1D log-Gabor filter as a basic feature. At the features extraction stage the features are generated from the ROI sub-images by filtering each row image with 1D log-Gabor filter. The results (real and imaginary parts), \( \Phi_r \) and \( \Phi_i \), are combined in the log-Gabor phase response, \( \Psi \), as follows:

\[ \Psi = \tan^{-1}\left(\frac{\Phi_i}{\Phi_r}\right) \]

Phase information is extracted using Eq. (2) and then quantized to obtain the binary phase feature or template.

C. Encoding process

The log-Gabor phase response, \( \Psi \), is qualitatively encoded as '1' or '0' based on the sign to obtain the template \( \varphi \). Therefore, each point in the \( \Psi \) is coded to one bit by the following inequalities:

\[ \varphi(i, j) = \begin{cases} 1 & \text{if } \Psi(i, j) \geq 0 \\ 0 & \text{if } \Psi(i, j) < 0 \end{cases} \]

Proposed feature extraction technique is showing in Fig. 2.

IV. Feature matching

Each palmprint spectrum is represented by a unique binary phase feature (Template). The matching between an input and a stored template consists of computing matching scores (degrees of similarity or dissimilarity) between them. The matching task in our experimental schemes based on a normalized hamming distance [8]. It is defined as the number of places where two vectors differ. we can define the Hamming distance \( D_h \) as:

\[ D_h = \frac{1}{N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} \varphi_t(i, j) \oplus \varphi_r(i, j) \]  

• \( \varphi_t, \varphi_r \) : The input and stored templates.
• \( \oplus \) : The Boolean operator (XOR).
• \( N_xN \) : Size of the templates.

It is noted that \( D_h \) is between 1 and 0. For perfect matching, the matching score is zero. In order to further reduce the variation of the translation, all the sub-images (ROI) are translated by some pixels (-2, -1, 1, 2).

V. Fusion at matching score level and image level

A. Fusion at matching score level

Fusion at the matching-score level is preferred in the field of biometrics because there is sufficient information content and it is easy to access and combine the matching scores [9]. In our system we adopted the combination approach, where the individual matching scores are combined to generate a single scalar score, which is then used to make the final decision. During the system design we experimented four different fusion schemes: Sum-score, Min-score, Max-score, Mul-score and Sum-weighting-score [10]. Suppose that the quantity \( D_{hi} \) represents the score of the \( i^{th} \) matcher (\( i = 1, 2, 3, 4 \)) for different palmprint spectrum (Blue, Green, Red and NIR) and \( F \) represents the fusion score. Therefore, \( F \) is given by:

- **Sum-Score (SUS):**
  \[ F = \sum_{i=1}^{n} D_{hi} \]
- **Min-Score (MIS):**
  \[ F = \min_i \{D_{hi}\} \]
- **Max-Score (MAS):**
  \[ F = \max_i \{D_{hi}\} \]
- **Mul-Score (MUS):**
  \[ F = \prod_{i=1}^{n} D_{hi} \]
- **Sum-Weighting-Score (SWS):**
  \[ F = \sum_{i=1}^{n} w_i D_{hi} \]

\[ w_i = \frac{1/\sum_{i=1}^{n} (1/EER_i)}{EER_i} \]

Where \( w_i \) denotes the weight associated with the matcher \( i \), with \( \sum_{i=1}^{n} w_i = 1 \), and \( EER_i \) is the equal error rate of matcher \( i \), respectively.
are averaged, as follow:

Approximation band and the three detailed bands of all images preserve the information from all the images, coefficients from images are fused as shown in Fig. 3 (for pairs of different palmprints found to match to the total number of match attempts. The False Rejection Rate (FRR) is the ratio of the number of instances of pairs of the same palmprint is found not to match to the total number of match attempts. FAR and FRR trade off against one another. That is, a system can usually be adjusted to vary these two results for a particular application, however decreasing one increase the other and vice versa. The system threshold value is obtained based on the Equal Error Rate (EER) criteria where FAR = FRR. This is based on the rationale that both rates must be as low as possible for the biometric system to work effectively. Another performance measurement is obtained from FAR and FRR which is called Genuine Acceptance Rate (GAR). It represents the identification rate of the system. In order to visually depict the performance of a biometric system, Receiver Operating Curves (ROC) are drawn. The ROC curve displays how the FAR changes with respect to the GAR and vice-versa [13]. Biometric systems generate matching scores that represent how similar (or dissimilar) the input is compared to the stored template.

VI. EXPERIMENTAL RESULTS AND DISCUSSION

A. EXPERIMENTAL DATABASE

Experiments are performed on the multispectral palmprint database from the Hong Kong polytechnic university (PolyU) [14]. The database contains images captured with visible and infrared light. Multispectral palmprint images were collected from 250 volunteers, including 195 males and 55 females. The age distribution is from 20 to 60 years old. It has a total of 6000 images obtained from about 500 different palms. These samples were collected in two separate sessions. In each session, the subject was asked to provide 6 images for each palm. Therefore, 24 images of each illumination from 2 palms were collected from each subject. The average time interval between the first and the second sessions was about 9 days.

B. PERFORMANCE OF IDENTIFICATION ALGORITHM

Identification occurs when the biometric system attempts to determine the identity of an individual. A biometric is collected and compared to all the templates in a database. Identification is closed-set if the person is assumed to exist in the database. In open-set identification, the person is not
Fig. 3. Multispectral image level fusion of Blue, Green and Red palmprint images.

Fig. 4. Single biometric identification test results. (a) The ROC curves for all spectrum palmprints, (b) The genuine and impostor distributions for NIR spectrum image and (c) The FAR-FRR depending on the threshold for NIR spectrum image.

guaranteed to exist in the database. In our work, the proposed method was tested through the second mode test (open-set). To evaluate the efficiency of this proposed method, the experiments were designed as follow: three palmprint images of each person were randomly selected for enrollment, and the rest, nine, palmprint images are used as test images for identification, respectively. The results are divided into two parts. First part presents the performance of the proposed palmprint identification algorithm for different variations on the images from four light spectrums (Red, Green, Blue, and NIR). Second part presents the performance of palmprint identification with the image fusion algorithms.

1) Single spectrum palmprint image: In this section we compare the performance of all spectrum images. In this experiment, the imposter and genuine distributions are generated by 1485 and 121770 comparisons, respectively. Fig. 4.(a) compares the performance of the system for deferent spectrums. It can safely be see the benefits of using the NIR spectrums than the Blue, Red and Green spectrums in terms of EER. For example, if only the Red spectrums are used, we have EER = 0.076 % at the threshold T_o = 0.350. In the case of using the Green spectrums, EER was 0.029 % at T_o = 0.365. The Blue spectrums done an EER equal to 0.024 % at T_o = 0.344. The use of NIR spectrums improves the result (0.011 % at T_o = 0.378) for a database size equal to 165. Therefore, the system can achieve higher accuracy at the NIR spectrums compared with the other spectrums of a palmprint. The results expressed as a FAR and FRR depending on the threshold values and the distance distributions of genuine and imposters matching obtained by the proposed scheme, if the NIR is used, are plotted in Fig. 4.(b) et Fig. 4.(c). Finally, Table 1 shows the FAR, FRR and GAR with percentage using Red, Green, Blue and NIR at deferent database size.

2) Multiple spectrum palmprint image: A robust identification system may require fusion of several spectrums for the reason that the limitation presented in one spectrum may be compensated by another spectrum. Multimodal identification system hence promises to perform better than any one of its individual components.

a) Performance of matching score level fusion algorithm: At the matching score level fusion, the matching scores output by multiple matchers are integrated. In our system, different combinations of spectrum images and fusion rules were tested to find the combination that optimizes the system accuracy.

- RGB fusion: In this experiment, only the Red, Green and Blue spectrums are used. To find the better of the all fusion rules, with the lowest EER, graphs showing the ROC curves were generated (see Fig. 5.(a)). This figure shows that the min rule offers better results in terms of the genuine acceptance rate. For example, if max rule is used, we have EER = 0.076 %. In the case of using Mul rule, EER was 0.006 %. Using sum and weighed rule, EER was 0.005 %. A min rule improves the result (0.004 %) for a database size equal to 165. Therefore, the system can achieve higher accuracy at the fusion of the two matching score compared with a single matching score. The genuine and impostor distributions are plotted in Fig. 5.(b). The system performance at all thresholds can be depicted in
TABLE 1: PERFORMANCE COMPARISON OF DIFFERENT SINGLE BIOMETRIC IDENTIFICATION SCHEMES

<table>
<thead>
<tr>
<th>Database</th>
<th>RED</th>
<th>GREEN</th>
<th>BLUE</th>
<th>NIR</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>FAR</td>
<td>FRR</td>
<td>GAR</td>
<td>FAR</td>
</tr>
<tr>
<td>100 Persons</td>
<td>0.005</td>
<td>0.250</td>
<td>99.990</td>
<td>0.000</td>
</tr>
<tr>
<td>165 Persons</td>
<td>0.000</td>
<td>0.227</td>
<td>99.997</td>
<td>0.024</td>
</tr>
</tbody>
</table>

(a) The ROC curves for all fusion rules and RGB combination, (b) The genuine and impostor distributions for MIS rule for RGB combination and (c) The FAR-FRR depending on the threshold for the MIS rule with RGB combination.

Fig. 5. Multimodal identification test results. (a) The ROC curves for all fusion rules and RGB combination, (b) The genuine and impostor distributions for MIS rule for RGB combination and (c) The FAR-FRR depending on the threshold for the MIS rule with RGB combination.

the form of FAR-FRR curve (see Fig. 5.(c)).

- **RGBN fusion:** In this experiment, all spectrums are used. The experiment showed that using the Max rule give a least identification rate (EER = 0.076 %), while all the rest fusion rule correctly classify all of the samples in our database (EER = 0.000 %). The average results of the two combinations in terms of EER are shown in Table 2.

<table>
<thead>
<tr>
<th>Method</th>
<th>RGB</th>
<th>RGBN</th>
</tr>
</thead>
<tbody>
<tr>
<td>SUS</td>
<td>0.005</td>
<td>0.000</td>
</tr>
<tr>
<td>MIS</td>
<td>0.004</td>
<td>0.000</td>
</tr>
<tr>
<td>MAS</td>
<td>0.076</td>
<td>0.076</td>
</tr>
<tr>
<td>MUS</td>
<td>0.006</td>
<td>0.000</td>
</tr>
<tr>
<td>SWS</td>
<td>0.005</td>
<td>0.000</td>
</tr>
</tbody>
</table>

*Fig. 6.* (a) Genuine and impostor distribution for RGB-DWT combination and the FAR-FRR depending on the threshold. Thus, the developed system is expected to give higher accuracy. The system was tested with different thresholds, combinations and fusion techniques and the results are shown in Table 3.

**VIII. Conclusion and Further Work**

A biometric system which is based only on a single biometric characteristic may not always be able to achieve the desired performance. A multi-biometric technique, which combines multiple modalities in making an identification, can be used to overcome the limitations. In this paper, a palmprint identification system is developed by using 1D log-Gabor method. The experimental results, obtained on a database size equal to 165 persons, show that it achieves a high
Fig. 6. Multimodal identification test results. (a) The ROC curves for RGBN, YN, RGB-Y combinations, and (b) The genuine and impostor distributions for RGB-DWT and (c) The FAR-FRR depending on the threshold for RGB-DWT.

**TABLE 3 : PERFORMANCE COMPARISON OF DIFFERENT MULTIPLE BIOMETRIC IDENTIFICATION SCHEMES**

<table>
<thead>
<tr>
<th>Database</th>
<th>RGB-Y</th>
<th>RGB-DWT</th>
<th>YN-DWT</th>
<th>RGBN-DWT</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>FAR</td>
<td>FRR</td>
<td>GAR</td>
<td>FAR</td>
</tr>
<tr>
<td>100 Persons</td>
<td>0.000</td>
<td>0.125</td>
<td>99.998</td>
<td>0.000</td>
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<tr>
<td></td>
<td>0.003</td>
<td>0.000</td>
<td>100.00</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>0.000</td>
<td>0.076</td>
<td>99.999</td>
<td>0.000</td>
</tr>
<tr>
<td>165 Persons</td>
<td>0.004</td>
<td>0.004</td>
<td>99.966</td>
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<tr>
<td></td>
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<td></td>
<td>0.006</td>
<td>0.000</td>
<td>99.995</td>
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</table>

For further improvement of the system, our future work will focus on the performance evaluation using large size database, and integration of multispectral palmprint information with other biometrics such as finger-knuckle-print to get security system with high accuracy.

**REFERENCES**


