Fusion of Finger-Knuckle-Print and Palmprint for an Efficient Multi-biometric System of Person Recognition

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Abstract—Biometric system has been actively emerging in various industries for the past few years, and it is continuing to roll to provide higher security features for access control system. Many types of unimodal biometric systems have been developed. However, these systems are only capable to provide low to middle range of security feature. Thus, for higher security feature, the combination of two or more unimodal biometrics (multiple modalities) is required. In this paper, we propose a multimodal biometric system for person recognition using hand images and by integrating two different modalities palmprint and Finger-Knuckle-Print (FKP). Addressing this problem we propose an efficient matching algorithm based on Phase-Correlation Function (PCF) and using the two biometric modalities the palmprint and the FKP. The two modalities are combined and the fusion is applied at the matching-score level. The experimental results showed that the designed system achieves an excellent recognition rate and provide more security than unimodal biometric-based system.

Index Terms—Multimodal Biometrics, Verification, Identification, FKP, Palmprint, PCF, Data Fusion.

I. INTRODUCTION

ONE of the primary functions of any security system is the control of people into or out of protected areas, such as physical buildings and information systems. Technologies called biometrics can automate the recognition of people by one or more of their distinct physical or behavioural characteristics. The term biometrics covers a wide range of technologies that can be used to verify person identity by measuring and analyzing human characteristics. Unimodal biometric systems perform person recognition based on a single source of biometric information. Such systems are often affected by some problems such as noisy sensor data and non-universality [1]. Thus, due to these practical problems, the error rates associated with unimodal biometric systems are quite high and consequently it makes them unacceptable for deployment in security critical applications.

Some of the problems that affect unimodal biometric systems can be alleviated by using multimodal biometric systems. Hand-based person identification provides a reliable, low-cost and user-friendly viable solution for a range of access control applications [2]. In fact, in contrast to other modalities like face and iris, the human hand contains a wide variety of modalities, which are fingerprint, hand geometry, palmprint and Finger-Knuckle-Print (FKP). These modalities can be by far used by biometric systems because of some advantages that the biometry of human hand offers [3]. First, data acquisition is relatively easy and economical via commercial low-resolution cameras. Second, hand-based access systems are very suitable for indoor and outdoor usage, and can work well in extreme weather and illumination conditions. Third, hand features of adults are more stable over time and they are not susceptible to major changes. Finally, human hand-based biometric information is very reliable and it can be successfully used for recognizing people among several populations.

Palmprint recognition is one kind of biometric technology and a relatively new biometric feature [4]. A simple palmprint biometric system has a sensor module, for acquiring the palmprint, a feature extraction module, for palmprint representation, and a matching module for decision making [5]. An ideal palmprint recognition system should be based on the fusion of several palmprint representations [6]. A FKP-based biometric recognition is more recent biometric technology and it has attracted an increasing amount of attention. The image-pattern formation of a finger-knuckle contains information that is capable of identifying the identity of an individual. The FKP biometric recognizes a person based on the knuckle lines and the textures in the outer finger surface. These line structures and finger textures are stable and remain unchanged throughout the life of an individual [7]. An important issue in FKP identification is to extract FKP features that can discriminate an individual from the other. There are many approaches for FKP identification using line-based and texture-based methods in various literatures.

This paper describes the prototype of a biometric recognition system based on a fusion of palmprint and FKP. For that, we propose to use Phase-Correlation Function (PCF) method for matching. The FKP and palmprint images are used as inputs of the matcher modules. The outputs of the matcher modules are combined using the concept of data fusion at matching score level. We have also tried the various fusion rulers to choose the best one for FKP and palmprint classification.

The remainder of this paper is organized as follows: The proposed multi-biometric scheme, using fusion at matching score level, is presented in section 2. The matching module, including an overview of the PCF and the decision module, is exposed in section 3. The obtained results are evaluated and commented in section 4. We conclude the paper, by stating the conclusions and perspectives, in the last section.
II. PROPOSED MULTI-BIOMETRIC SYSTEM

Fig. 1 shows the block diagram of the proposed multimodal biometric recognition system. It is based on the fusion of FKP and palmprint images at the matching-score level. Multimodal biometric recognition scheme involves, for both FKP and palmprint modalities, image pre-processing module and matching module. The matching between the verified ROI and registered one in database, for both FKP and Palmprint, is performed using PCF. Matching scores from both unimodal biometric recognition systems are combined into a unique matching score using fusion at the matching-score level. Based on this unique matching score, a final decision is made (the user is identified or rejected). This improved structure takes advantage of the proficiency of each unimodal biometric and can be used to overcome some of their limitations.

III. PCF-BASED MATCHING

Frequency-domain palmprint matching is based on the 2D Discrete Fourier Transform (2D DFT) property. It consists of translational displacement in the spatial domain that corresponds to a linear phase shift in the frequency domain \([8]\). Let tow \(N_1 \times N_2\) images, the palmprint image to be verified (current), noted by \(f_v\), and the registered palmprint image, (reference), noted by \(f_r\). Thus, assuming that these two images are different upon a moving area, which we note it here by \(\mathcal{D}\), only due to a translational displacement \((\tau_1, \tau_2)\).

\[
f_v(n_1, n_2) = f_v(n_1 + \tau_1, n_2 + \tau_2), \quad (n_1, n_2) \in \mathcal{D} \tag{1}
\]

By taking the 2D DFT of both sides, with respect to the spatial variables \((n_1, n_2)\), we obtain, in frequency domain, the following equation of the frequency variables \((k_1, k_2)\):

\[
F_v(k_1, k_2) = F_r(k_1, k_2) e^{j(-k_1 \tau_1 - k_2 \tau_2)} \tag{2}
\]

Where \(F_v\) and \(F_r\) are the Fourier transform (FT) of the palmprint image to be verified (current) and the registered palmprint image (reference), respectively. If we define \(\Delta \phi(k_1, k_2)\) as the phase difference between the FT of the current image and that of the reference one, then we have:

\[
e^{j\Delta \phi(k_1, k_2)} = e^{j[\phi_v(k_1, k_2) - \phi_r(k_1, k_2)]}
\]

\[
e^{j\Delta \phi(k_1, k_2)} = e^{j\phi_v(k_1, k_2)}, e^{-j\phi_r(k_1, k_2)}
\]

\[
F_v(k_1, k_2) \cdot \frac{F_r^*(k_1, k_2)}{|F_v(k_1, k_2)|} \quad \text{and} \quad F_r^*(k_1, k_2) \cdot \frac{F_v^*(k_1, k_2)}{|F_r^*(k_1, k_2)|} \tag{3}
\]

Where \(\phi_v\) and \(\phi_r\) are the phase components of \(F_v\) and \(F_r\), respectively, and the superscript * indicates the complex conjugate. If we define \(C_{v,r}(n_1, n_2)\) as the inverse DFT of \(e^{j\Delta \phi(k_1, k_2)}\), this permits to have:

\[
C_{v,r}(n_1, n_2) = \mathcal{F}^{-1}\{e^{j\Delta \phi(k_1, k_2)}\}
\]

\[
\mathcal{F}^{-1}\{e^{j\phi_v(k_1, k_2)} \cdot e^{-j\phi_r(k_1, k_2)}\}
\]

\[
\mathcal{F}^{-1}\{e^{j\phi_v(k_1, k_2)} \} \otimes \mathcal{F}^{-1}\{e^{-j\phi_r(k_1, k_2)}\} \tag{4}
\]

Where \(\otimes\) is the 2D convolution operation. In other words, \(C_{v,r}(n_1, n_2)\) is the cross-correlation of the inverse 2D Discrete Fourier Transform (\(\mathcal{F}^{-1} = 2D-IDFT\)) of the phase components of \(F_v\) and \(F_r\). For this reason, \(C_{v,r}(n_1, n_2)\) is known as the Phase Correlation Function (PCF) \([9]\). The importance of this function becomes apparent if it is rewritten in terms of the phase difference in equation (2):

\[
C_{v,r}(n_1, n_2) = \mathcal{F}^{-1}\{e^{j\Delta \phi(k_1, k_2)}\}
\]

\[
= \mathcal{F}^{-1}\{e^{j(-k_1 \tau_1 - k_2 \tau_2)}\} = \delta(n_1 - \tau_1, n_2 - \tau_2) \tag{5}
\]

Thus, the phase correlation surface has a distinctive impulse at \((\tau_1, \tau_2)\). This observation is the basic idea behind the phase correlation matching. In this method, equation (3) is used to calculate \(e^{j\Delta \phi(k_1, k_2)}\), the 2D-IDFT is then applied to obtain \(C_{v,r}(n_1, n_2)\) and the location of the impulse in this function is detected to estimate \((\tau_1, \tau_2)\) When the two images are similar, their PCF gives a distinct sharp peak. When the two images are not similar, the peak drops significantly. Thus, the PCF exhibits much discrimination capability than the ordinary correlation function. The height of the peak can be used as a good similarity measure for image matching.

IV. EXPERIMENTAL RESULTS: EVALUATION AND COMMENTS

To evaluate the performance of the proposed multi-modal biometric recognition scheme, a database containing palmprint and FKP images has been created. We have constructed a multi-biometric database for our experiments using the palmprint database and the FKP database both from the Hong Kong Polytechnic University (PolyU database \([10], [11]\)). The multi-biometric database consists of 12 FKP images and 12 palmprint images per person of 150 persons. Note that, in order to establish a comparative study between unimodal biometric system and multimodal biometric system, we have used the same databases for evaluating the two systems.

Fig. 1. The block diagram of the proposed palmprint and FKP-based biometric recognition system.
A. Verification tests

For the verification tests, the FKP and palmprint images of the experiment database were divided into two parts: 3 of 12 images were randomly selected in the enrolment stage to create the client database; the remaining 9 images were used for testing. Thus, the genuine distribution and impostor distribution are generated by 1350 and 201150 comparisons, respectively. At the verification stage, a threshold $T_o$ is used to regulate the system decision. The system infers that pairs of biometric samples generating scores higher than or equal to $T_o$ are mate pairs (that is, they belong to the same person). Consequently, pairs of biometric samples generating scores lower than $T_o$ are non-mate pairs (that is, they belong to different persons). The distribution of scores generated from pairs of samples from different persons is called an impostor distribution; the score distribution generated from pairs of samples from the same person is called a genuine distribution.

1) Verification in the case of unimodal biometric system: An unimodal biometric system is a biometric system that utilizes only one biometric modality (FPK or palmprint in our case). The objective of this section is to evaluate the performance of the unimodal system by using separately the FKP biometry or the palmprint biometry.

a) FKP verification: The goal of this experiment was to evaluate the system performance when using information from each finger type. For this, we found the performance under different modalities Left Index Finger (LIF), Left Middle Finger (LMF), Right Index Finger (RIF) and Right Middle Finger (RMF). By adjusting the matching threshold, a Receiver Operating Characteristic (ROC) curve, which is a plot of False Reject Rate (FRR) against False Accept Rate (FAR) for all possible thresholds, can be created. Fig. 2(a) compares the performance of the system for all finger types. The experimental results indicate that the RIFs perform better than the RMFs, LIFs and LMFs in terms of EER. For example, if only the RMF is used, we have EER = 7.198% at the threshold $T_o = 0.066$. In the case of using the LIF, EER was 9.464% at $T_o = 0.067$. The LMF made an EER equal to 7.198% at $T_o = 0.066$. The use of RIFs improves the result (5.688% at $T_o = 0.061$) for a database size equal to 165. The distance distributions of genuine and imposter matchings obtained by the proposed scheme, if the RIF is used, are plotted in Fig. 2(b). Fig. 2(c) presents the corresponding ROC.

b) Palmprint verification: For the evaluation of the system performance, in the case of palmprint as alone input of biometric data, the genuine and impostor distributions are plotted in Fig. 3(a). The results expressed as a FAR and FRR depending on the threshold values is plotted in Fig. 3(b). The system performance at all thresholds can be depicted in the form of a ROC curve (see Fig. 3(c)). The described recognition system can achieve an EER equal to 0.606% at the decision threshold $T_o = 0.049$, and a maximum Genuine Acceptance Rate (GAR) equal to 99.394%.

2) Verification in the case of multimodal biometric system: The objective of this section was to investigate the integration of the two biometric modalities: FKP and palmprint in the biometric recognition system in order to achieve a better performance that may not be achievable by using only one of the two biometric modalities. In the matching score level, different rules such as Sum, Weighted, Min and Max rules can be used to combine scores obtained by biometric systems. Such approaches provide significant performance improvement. In the weighted rule, for example if $D_0$ and $D_1$ represent the normalized scores pertaining to the RIF and palmprint modalities, respectively, then the final score, $S_F$, is computed as:

$$S_F = w_0D_0 + w_1D_1$$  \hspace{1cm} (6)

Here $w_0$ and $w_1$ are the weights associated with the tow units,

$$w_i = \frac{EER_i}{\sum_{k=0}^{k} EER_k}$$  \hspace{1cm} (7)

Where $i = 0; 1$, $w_0 + w_1 = 1$ and the $EER_k$ is the unimodal biometric error.

The ROCs illustrating the performance from different fusion rules are shown in Fig. 4(a). The ROCs from individual fusions suggest that sum rule has performed better than other. As expected, the max and min rule shows poor performance than other rules (sum and weighted). Fig. 4(b) shows the genuine and impostor distributions for FKP and palmprint when using the method of sum rule. Finally, Fig. 4(c), for example, if only the RIF is used, we have GAR = 94.312%, in case of using palmprint, GAR was 99.394%. In the case of using the fusion (at the score level by using sum rule) of FKP and palmprint, GAR was 99.647% at the decision threshold $T_o = 0.136$.

B. Identification test

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 guaranteed to exist in the database [12]. In our work, the proposed method was tested through the second mode test (open-set).

a) Decision module for identification: Prior to finding the decision, a Min-Max normalization scheme was used to transform the computed score vectors. Therefore, these scores are compared and the highest score provides the identity of the test FKP or palmprint image. Suppose that the score vector is given by:

$$D_i = [D_{i0} \ D_{i1} \ D_{i2} \ D_{i3} \cdots D_{iN}]$$  \hspace{1cm} (8)

Where $N$ represents the size of system database and $i$ the image test. Then, the Min-Max normalization scheme is given by:

$$DN_i = \frac{D_i - \text{Min}(D_i)}{\text{Max}(D_i) - \text{Min}(D_i)}$$  \hspace{1cm} (9)

Where $DN$ represents the normalized vector.

b) Identification in the case of unimodal system: To evaluate the efficiency of the unimodal system, the genuine distribution and impostor distribution are generated by 1350 and 201150 comparisons, respectively.

✓ FKP identification: In this experiment, the performances under different modalities LIF, LMF, RIF and RMF are
evaluated. A ROC curve for all possible thresholds is shown in Fig. 5(a). From this figure, it can be seen that the described identification system achieves, for a database size equal to 165 persons, a best EER equal to 2.583 % at the decision threshold \( T_o = 0.544 \) when the RIF modalities are used. The genuine and imposter distributions are shown in Fig. 5(b). Fig. 5(c) presents the dependency of the FAR on the threshold value. From Fig. 5(c) it can be seen that the identification system achieves a GAR equal to 97.417 %.

✓ Palmprint identification: Fig. 6(a) shows the two distributions under different thresholds. Fig. 6(b) presents the dependency of the FAR and the FRR on the threshold value and Fig. 6(c) represents the ROC curve. Our identification system can achieve an EER of 0.337 % for \( T_o = 0.309 \) and the maximum GAR = 99.663 %. The developed system is expected to give higher accuracy.

c) Identification in the case of multimodal biometric system: We plot the ROC curve in Fig. 7(a). It can safely be seen the benefits of using the fusion of FKP and palmprint. The performance of the identification system is significantly improved by using the fusion with sum rule method. For example, if FKP is used for the identification, we have EER = 3.713 % for the threshold equal to 0.576. In the case of using palmprint, EER was 0.337 % at the threshold \( T_o = 0.876 \). Thus, a fusion scheme improves the result (EER = 0.003 % at the \( T_o = 0.876 \)) for a database size equal to 165. The distance distributions of genuine and imposter matchings obtained by the proposed scheme are plotted in Fig. 7(b). Fig. 7(c) presents the corresponding ROC curves.

V. CONCLUSION

In this paper, we have designed a biometric recognition system based on the fusion of FKP and palmprint modalities. The scheme uses the PCF for matching process. Fusion at the matching-score level improves the performance of the system. A database of 156 persons was used for testing the system. The experimental results showed that information fusion at the matching score level improves the results of the identification. The obtained results showed that the proposed system has the
Fig. 5. Unimodal identification test results “FKP biometric”. (a) The ROC curves for all finger types, (b) The genuine and impostor distribution and (c) The ROC curves for the RIF modalities

Fig. 6. Unimodal identification test results “Palmprint biometric”. (a) The genuine and impostor distribution, (b) The dependency of the FAR and the FRR on the threshold value and (c) The ROC curves for the Palmprint modalities

Fig. 7. Multimodal identification test results. (a) The ROC curves based on RIF and Palmprint fusion, (b) The genuine and impostor distribution and (c) The ROC curves for the fusion scheme

capacities to be used in the environments that require a high security.

REFERENCES


