Hybrid Multi-Biometric Person Authentication System

Tran Binh Long, Le Hoang Thai

***Abstract*—In this paper, the authors present a hybrid multi-biometric authentication person system that integrates both multi modal and multi algorithmic. Multi-modal, the system using face and fingerprint features, has long been considered common in personal authentication. Multi-algorithm is the system which uses Circularly Orthogonal Moments, such as Zernike Moment (ZM), Pseudo Zernike Moment (PZM), Polar Cosine Transform (PCT) and Radial Basis Function (RBF) Neural Networks. These moments are widely used because their magnitudes are invariant to image rotation, scaling and noise. With such incorporation of multi-modal and multi-algorithms, our proposed system is expected to minimize the possibility of forge in authentication better than uni-biometric systems. In reference to this expectation, the experimental results have demonstrated that our method can assure a higher level of forge resistance than that of the systems using single biometric traits.**

***Index Terms*—Multi-biometrics, Personal Authentication, Face, Fingerprint, Circularly Orthogonal Moments.**

I. INTRODUCTION

Biometrics refers to automatic identification of a person based on his physiological or behavioral characteristics [1],[2]. Thus, it is inherently more reliable and more capable of differentiating between an authorized person and a fraudulent imposter [3]. Biometric-based personal authentication systems have gained intensive research interest for the fact they are more secure and more convenient than traditional systems which use passwords, pin numbers, key cards and smart cards [4] in that they can't be borrowed, stolen or even forgotten. Currently, there are different biometric techniques either widely-used or under development, including face, facial thermo-grams, fingerprint, hand geometry, hand vein, iris, retinal pattern, signature, and voice-print (Figure 1) [3],[5]. Each of these biometric techniques has its own advantages and disadvantages and hence is admissible, depending on the application domain. However, a proper biometric system to be used in a particular application should possess the following distinguishing traits: uniqueness, stability, collectability, performance, acceptability and forge resistance [6].

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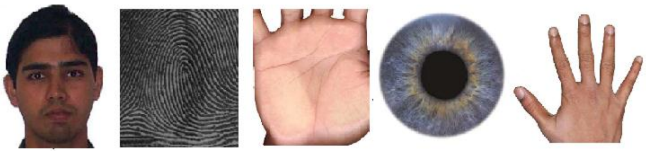

Fig. 1. Examples of biometric characteristic

Most of currently-used biometric systems employ single biometric trait; these systems are called uni-biometric. Despite their considerable advancement in recent years, there are still challenges that negatively influence their resulting performance, such as noisy data, restricted degree of freedom, intra-class variability, non-universality, spoof attack and unacceptable error rates. Some of these restrictions can be lifted by multi-biometric systems [7] which utilize more than one physiological or behavioral characteristic for enrollment and verification/ identification, such as (i) multiple sensors, (ii) multiple representations or multiple algorithms, (iii) multiple instances, (iv)multiple samples, and (v) multiple biometric traits.

Those multi-biometric systems can remove some of the drawbacks of the uni-biometric systems by grouping the multiple sources of information [8]. In the first four scenarios, multiple sources of information are derived from the same biometric trait. In the fifth scenario, information is derived from different biometric traits, which gives the system the name of Multimodal. In fact, biometric fusion can also be carried out in any arbitrary combination of the above five sources and such systems can be referred to as hybrid multi-biometric systems [9]. So this system is basically multi-algorithmic as well as multimodal in its design. And it is the focus of our study.

Multi-biometric systems are gaining acceptance among designers and practitioners due to (i) their performance superiority over uni-modal systems, and (ii) the admissible and satisfactory improvement of their system speed. Accordingly, it is hypothesized that our employment of multiple modalities (face and fingerprint) and multiple algorithms (ZM, PZM, PCT, RBF) can conquer the limitations of the single modality- based techniques. Under some hypotheses, the combination scheme has proven to be superior in terms of accuracy; nevertheless, practically some precautions need to be taken as Ross and Jain [7] put that multi-biometrics has various levels of fusion, namely sensor level, feature level, matching score level and decision level. In this paper, we proposed a method using hybrid multi-biometrics with decision level fusion. Our work aims at investigating how to combine the features extracted from different modalities. Zernike Moment (ZM)[10] Pseudo Zernike Moment (PZM)[11] and Polar Cosine Transform (PCT)[12] were used to extract both face and fingerprint

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features as follows: First, the basis functions of Zernike moment (ZM), Pseudo Zernike Moment (PZM) and Polar Cosine Transform (PCT) were defined on a unit circle. Namely, the moments were computed in circular domains. Next, for each biometric trait, the separate authentication decision was carried out by Radial Basis Function (RBF) neural networks, and the outputs of the each RBF neural network were combined. In this stage, the majority method was used for authentication decision strategy. The decisions were at last fused with AND rule. The AND rule requires a positive decision from all verification modules, so it will not only lead to low false authentication rates, but also result in high false rejection rates.

The remainder of the paper is organized as follows: section 2 describes the methodology; section 3 reports and discusses the experimental results, and section 4 presents the conclusion.

II. METHODOLOGY

Our hybrid multi-biometric authentication system is composed of two phases which are enrollment and verification. Both phases involve pre-processing for face and fingerprint images, extracting the feature vectors invariant parallel with ZM, PZM, PCT, making decision with RBF, and fusing at decision level. (Figure 2)

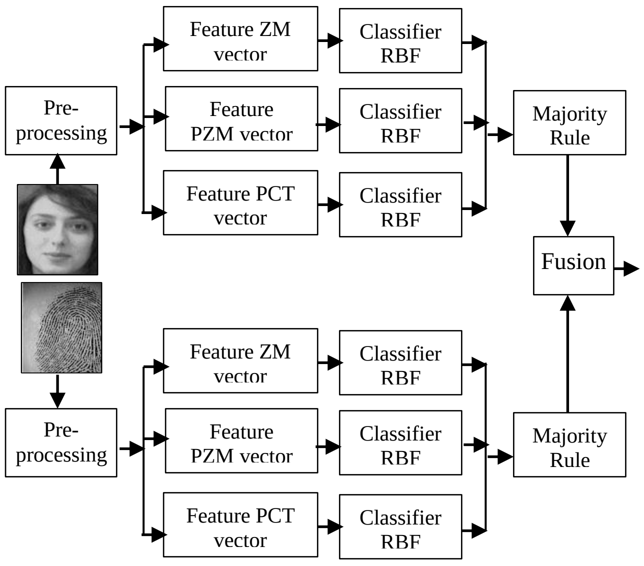

Fig. 2. The chart for face and fingerprint authentication system

A. *Preprocessing*

The purpose of the pre-processing is to reduce or eliminate some of the image variations for the illumination of the image. In this stage, the image was preprocessed before feature extraction. Our hybrid multi-biometric authentication system uses histogram equalization, wavelet transform [13] to preprocess the image normalization, noise elimination, illumination normalization etc. Wavelet transform is a representation of a signal in terms of a set of basic functions, obtained by dilation and translation of a basis wavelet. Since wavelets are short-time oscillatory functions with finite support length (limited duration both in time and frequency), they are localized in both time (spatial) and frequency domains. The joint spatial-frequency resolution obtained by wavelet transform makes it a good candidate for the extraction of details as well as approximations of images. In the two-band multi-resolution wavelet transform, signals can be expressed by wavelet and scaling basis functions at different scale, in a hierarchical manner. (Figure 3)

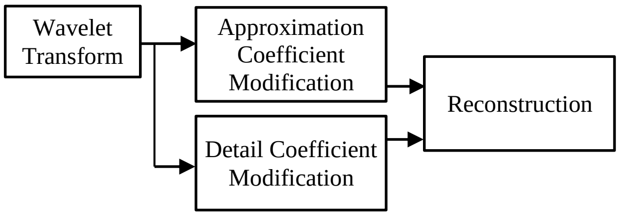

Fig. 3. Block diagram of normalization

$$f(x) = \sum_k a_{0,k} \emptyset_{0,k}(x) + \sum_j \sum_k d_{j,k} \psi_{j,k}(x) \qquad (1)$$

$\emptyset_{j,k}$ are scaling functions at scale j and $\psi_{j,k}$ are wavelet functions at scale j. $a_{j,k}$, $d_{j,k}$ are scaling coefficients and wavelet coefficients.

After the application of wavelet transform, the derived image was decomposed into several frequency components in multi-resolution. Using different wavelet filter sets and/or different number of transform-levels brings about different decomposition results. Since selecting wavelets is not the focus of this paper, 1-level db10 wavelets were randomly chosen for our experiments. In fact, any wavelet-filters can be used in the proposed method.

B. *Feature extraction*

In order to design a good face recognition system, the choice of feature extractor is very crucial. The feature vectors should contain the most pertinent information about the recognized face and fingerprint. In our method, different features were extracted from the derived image normalization (feature domain) in parallel structure with the use of Circularly Orthogonal Moment (COM). Among them, three different kinds of feature domains- PZM, ZM and PCT [14][15][16]- were selected. Therefore, in this approach more characteristics of face and fingerprint images can be extracted for recognition.

Given a 2D image function f(x, y), it can be transformed from Cartesian coordinate to polar coordinate f(r, θ), where r and θ denote radius and azimuth respectively. The following formulae transform from Cartesian coordinate to polar coordinate,

$$r = \sqrt{x^2 + y^2}, \qquad (2)$$

and

$$\theta = \arctan(\frac{y}{x}) \qquad (3)$$

Image is defined on the unit circle that $r \leq 1$, and can be expanded with respect to the basis functions $V_{nl}(r, \theta)$.

Zernike Moment

For an image $f(x, y)$, it is first transformed into the polar coordinates and denoted by $f(r, \theta)$. The Zernike moment with order n and repetition l is defined as

$$M_{nl} = \frac{n+1}{\pi} \int_0^{2\pi} \int_0^1 [V_{nl}(r, \theta)]^* f(r, \theta) r dr d\theta \qquad (4)$$

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Where * denotes complex conjugate, n = 0, 1, 2. . . ∞, l is an integer subject to the constraint that n - |l| is nonnegative and even. $V_{nl}(r,\theta)$ is the Zernike polynomial, and it is defined over the unit disk as follows:

$$V_{nl}(r,\theta) = R_{nl}(r)e^{il\theta} \tag{5}$$

With the radial polynomial $R_{nl}(r)$ defined as

$$R_{nl}(r) = \sum_{s=0}^{\frac{(n-|l|)}{2}} \frac{(-1)^s (n-s)!\, r^{n-2s}}{s!\left(\frac{n+|l|}{2}-s\right)!\left(\frac{n-|l|}{2}-s\right)!} \tag{6}$$

The kernels of ZMs are orthogonal so that any image can be represented in terms of the complex ZMs. Given all ZMs of an image, it can be reconstructed as follows:

$$f(r,\theta) = \sum_{n}\sum_{(All\ l's)} M_{nl}V_{nl}(r,\theta) \tag{7}$$

Pseudo Zernike Moment

PZM is similar to ZM except that the radial polynomial is defined as

$$R_{nl}(r) = \sum_{s=0}^{n-|l|} \frac{(-1)^s (2n+1-s)!\, r^{n-s}}{s!\,(n-|l|-s)!\,(n+|l|+1-s)!} \tag{8}$$

Where n = 0, 1, 2, . . , ∞, and l is an integer subject to constraint |l|≤ n only.

Polar Cosine Transform

Polar Cosine Transform is given by

$$f(r,\theta) = \sum_{n=0}^{\infty}\sum_{l=-\infty}^{\infty} M_{nl}V_{nl}(r,\theta) \tag{9}$$

where the coefficient is

$$M_{nl} = \Omega_n \int_0^{2\pi}\int_0^{1} f(r,\theta)V_{nl}^{*}(r,\theta)\, r dr d\theta \tag{10}$$

the basis function is given by

$$V_{nl}(r,\theta) = R_n(r)e^{il\theta} \tag{11}$$

where

$$R_n(r) = \cos(\pi n r^2) \tag{12}$$

and

$$\Omega_n = \begin{cases} \frac{1}{\pi} & \text{if } n = 0 \\ \frac{2}{\pi} & \text{if } n \neq 0 \end{cases} \tag{13}$$

rewrite (10),

$$M_{nl} = \Omega_n \int_0^{2\pi}\int_0^{1} f(r,\theta)\cos(\pi n r^2)\left(\cos(l\theta) - i\sin(l\theta)\right) r dr d\theta \tag{14}$$

C. Simulation

It is known from the experiment that PCT can perform better than ZM and PZM. In practice, when the orders of ZM and PZM exceed a certain value, the quality of the reconstructed image degrades quickly because of the numerical instability problem inherent with ZM and PZM. By comparison, the PCT does not have this problem. Due to this observation, we decided to choose the order of ZM equate to 35 with 36 feature vector elements and the order of PZM equal to 20 with 21 feature vector elements. In this way, ZM and PZM can perform better, and PCT is similar to PZM. (Figure 4)

Fig. 4. Example of ZM for feature extraction with face and fingerprint

D. Classification

In this paper, an RBF neural network was used as a classifier in the face and fingerprint recognition system in which the inputs to the neural network are the feature vectors derived from the proposed feature extraction technique described in the previous section.

RBF Neural Network Description.

RBF neural network (RBFNN)[17][18] is a universal approximator that is of the best approximation property and has a very fast learning speed thanks to locally- tuned neurons (Park and Wsandberg, 1991; Girosi and Poggio, 1990; Huang, 1999a; Huang, 1999b). Hence, RBFNNs have been widely used for function approximation and pattern recognition.

A RBFNN can be considered as a mapping: $\Re^r \to \Re^s$. Let $P \in \Re^r$ be the input vector, and $C_i \in \Re^r$ $(1 \ll i \ll u)$ be the prototype of the input vectors, then the output of each RBF unit can be written as:

$$R_i(P) = R_i(\|P - C_i\|) \quad i = 1,\dots,u \tag{15}$$

where || . || indicates the Euclidean norm on the input space. Usually, the Gaussian function is preferred among all possible radial basis function due to the fact that it is factorable. Thus,

$$R_i(P) = \exp\left(-\frac{\|P-C_i\|^2}{\sigma_i^2}\right) \tag{16}$$

where σ_i is the width of the ith RBF unit. The jth output $y_i(P)$ of a RBFNN is

$$y_i(P) = \sum_{i=1}^{u} R_i(P) \times w(j,i) \tag{17}$$

where w(j,i) is the weight of the jth receptive field to the jth output.

In our experiments, the weight w(j,i), the hidden center Ci and the shape parameter of Gaussian kernel function σ_i were all adjusted in accordance with a hybrid learning algorithm

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combining the gradient paradigm with the linear least square (LLS)[19] paradigm.

System Architecture of the Proposed RBFNN.

In order to design a classifier based on RBF neural network, a fixed number of input nodes was set in the input layer of the network. This number is equal to that of the combined feature vector elements. Also, the number of nodes in the output layer was set to be equal to that of the image classes, equivalent to 8 combined fingerprint and facial images. The selected RBF units are equal to the set number of the input nodes in the input layer.

For neural network 1: the amount of feature vector elements of ZM is 36, corresponding to 36 input nodes of input layer; the chosen number of RBF units of hidden layer is 36; the number of nodes in the output layer is 8.

For neural network 2 and 3: the quantity of feature vector elements of PZM is 20, corresponding to 21 input nodes of input layer; the chosen number of RBF units of hidden layer is 21; the number of nodes in the output layer is 8.

The extraction of feature domains and the performance of these RBF neural networks take place in parallel structure. The outputs from each RBF neural network are then combined to construct the identification.

E. *Decision level fusion*

With the use of multiple modalities, fusion techniques should be established for combining the different modalities. Integration of information in a Multimodal biometric system can occur in various levels, namely sensor level, feature level, matching level or decision level [20]. At the sensor or feature level, the feature sets of different modalities are combined. Fusion at this level provides the highest flexibility, but classification problems may arise due to the large dimension of the combined feature vectors. Fusion at matching level is the most common one, whereby the scores of the classifiers are usually normalized and then combined in a consistent manner. For the decision-level fusion, each subsystem determines its own authentication decision and all individual results are combined to a common decision of the fusion system.

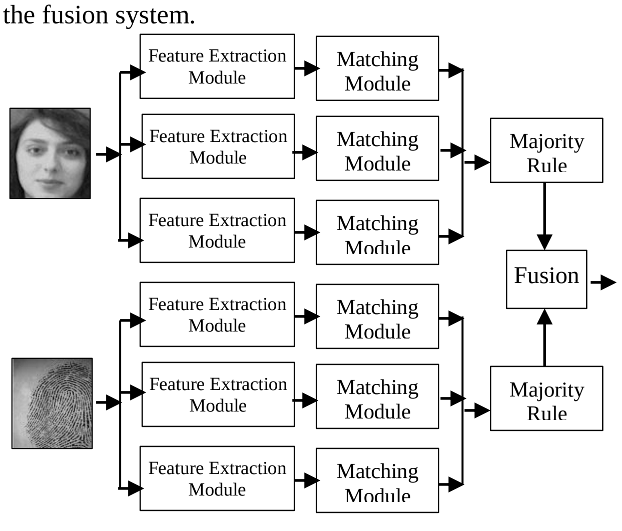

Fig. 5. Sample face images from ORL face database

In this study, fusion at the decision level is applied for data fusion of the various modalities, based on the majority vote rule. For three samples, as is the case, a minimum of two accept votes is needed for acceptance. Also, for the final fusion, the AND rule is used. Figure 5 shows fusion level applied in this study.

III. EXPERIMENTAL RESULTS

A. *Database of the experiment*

Our experiment was conducted on the public domain fingerprint images dataset DB4 FVC2004 [21], ORL face database [22].

Fig. 6. Sample fingerprint images from FVC 2004 database

Fig. 7. Sample face images from ORL face database

In DB4 FVC2004 database, the size of each fingerprint image is 288x384 pixels, and its resolution is 500 dpi. FVC2004 DB4 has 800 fingerprints of 100 fingers (8 images of each finger). Some sample fingerprint images used in the experimentation were depicted by Figure 6.

ORL face database is comprised of 400 images of 40 persons with variations in facial expressions (e.g. open/close eyes, smiling/non-smiling), and facial details (e.g. with wearing glasses/without wearing glasses). All the images were taken on a dark background with a 92 x 112 pixels resolution. Figure 7 shows an individual’s sample images from the ORL database.

With the assumption that certain face images in ORL and fingerprint images in FVC belong to an individual, in our experiment, we used 320 face images (8 images from each of 40 individuals) in ORL face database, and 320 fingerprint images (8 images from each of 40 individuals) in FVC fingerprint database. Combining those images in pairs, we have our own database of 320 double images from 40 different individual, 8 images from each one, which we named ORL-FVC database.

B. *Evaluation*

The test of the proposed biometric recognition system consists in the evaluation of the feature extraction modules, the matching modules and the fusion block represented in Figure 5.

In this section, the capabilities of the proposed Hybrid approach in multi-biometric authentication were demonstrated. A sample of the proposed system with three different feature domains and of the RBF neural network was developed. In this example, for the PZM and ZM, all moments from order 20 to 35 were considered as feature vector elements. The chosen feature vectors for these domains were 21 elements for the PZM and 36 for the ZM.

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Also, for the PCT feature vector, 21 elements from each image were created. The proposed method was evaluated in terms of its recognition performance with the use of ORL-FVC database. Five images of each of 40 individuals in the database were randomly selected as training samples while the remaining samples without overlapping were used as test data. Consequently, we had 200 training images and 120 testing images for RBF neural network for each trial. Since the number of the ORL-FVC database is limited, we performed the trial over 3 times to get the average authentication rate. Our achieved authentication rate is 96.75% (Table I).

TABLE I.
RECOGNITION RATE OF OUR PROPOSED METHOD

Test	Rate
1	97.14%
2	96.29%
3	96.82%
Mean	96.75%

In our paper, the effectiveness of the proposed method was compared with that of the mono-modal traits, typically human face recognition systems [23], and fingerprint recognition systems [24], in which ZM has 36 feature elements, and the PZM as well as the PCT has 21 elements. It can be seen from the comparative results of mono-modal traits shown in Table II that the recognition rate of our hybrid multi-biometric system is much better than that of any other individual recognition.

TABLE II
THE FAR,FRR AND ACCURACY VALUES OBTAINED FROM THE MONO-MODAL TRAITS

Trait	FRR(%)	FAR(%)	Accuracy
Face[21]	13.47	11.52	73.20
Fingerprint[22]	7.151	7.108	92.892

Also in our work, we conducted separated experiments on the technique of face, fingerprint, fusion at matching score and decision level. The comparison between the achieved accuracy of our proposed technique with that of each mentioned technique has indicated its striking usefulness and utility. (See in Figure 8)

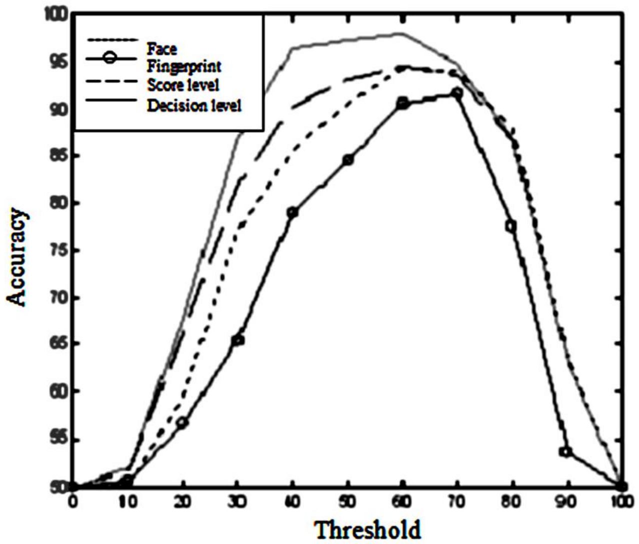

Fig. 8. The Accuracy curve of face, fingerprint, fusion at score and decision level

For the recognition performance evaluation, a False Acceptance Rate (FAR) and a False Rejection Rate (FRR) test were performed. These two measurements yield another performance measure, namely Total Success Rate (TSR):

$$\mathrm{TSR} = \left(1 - \frac{\mathrm{FAR+FRR}}{\text{total number of accesses}}\right) \times 100\% \qquad (18)$$

The system performance was evaluated by Equal Error Rate (EER) where FAR=FRR. A threshold value was obtained, based on Equal Error Rate criteria where FAR=FRR. Threshold value of 0.2954 was gained for ZM-PZM-PCT- RBF as a measure of dissimilarity.

Table III shows the testing results of verification rate with the ZM comprising of 36 feature elements, the PZM as well as the PCT including 21 elements, and the obtained threshold value.

The results demonstrate that the application of ZM, PZM and PCT as feature extractors can best perform the recognition.

TABLE III
TESTING RESULT OF AUTHENTICATION RATE OF MULTIMODAL

Method	**Thres**	**FAR(%)**	**FRR(%)**	**TSR(%)**
Proposed method	0.2954	4.95	1.12	96.75

IV. Conclusion

This paper has outlined the possibility to augment the verification accuracy by using hybrid multiple biometric. In the paper, the authors have presented a novel approach in which multiple modalities (fingerprint and face images) were processed with multiple algorithms (Zernike Moment, Pseudo Zernike Moment, Polar Cosine Transform and Radial Basis Functions) to obtain comparable features. The reported experimental results have demonstrated a remarkable improvement in the accuracy level achieved from the proper fusion of decision sets. It is also noted that fusing information from independent/ uncorrelated sources (face and fingerprint) at the decision level fusion with AND rule enables better authentication than doing it with OR. This preliminary achievement does not constitute an end in itself, but suggests an attempt of a multi-biometric data fusion as early as possible in parallel processing. However, the real feasibility of this approach, in a real application scenario, may heavily depend on the physical nature of the acquired signal; thus, it is assumed that further experiments on “standard” multimodal databases will allow better validation of the overall system performances. If it takes place, our proposed method can be used with existing uni-biometric systems to increase rate authenticate against tampering.

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