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Feature level Fusion of Face and Hand for Multibiometric Based Personal Identification

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Abstract— Unimodal biometric systems have several inherent problems such as intra-class variation, noisy-sensor data, spoofing attacks and non-universality. To overcome this limitation multibiometric is a good option where we can use two or more individual modalities. In this paper we propose a multibiometric system for personal identification based on feature level fusion of face and hand. Information from multiple sources can be consolidated in several distinct levels including feature level, score level and decision level. Feature level fusion is considered more powerful and effective than the other level of fusion like score and decision level fusion. The main reason of its effectiveness is the feature set contains richer information about the input biometric data. Feature level fusion is expected to provide better recognition result. However score level fusion and decision level fusion are more popular in the literature and there is not much research on feature level fusion. In this paper, we discuss fusion at feature level in 2 different scenarios: (i) fusion of PCA and LDA coefficients of face ;(ii) fusion of face and hand. The experiment result shows that performance of the LDA-based matcher is much higher than that of the PCA-based matcher.

Keywords: Unimodal, multibiometric, face, hand, feature level fusion, score level fusion, PCA, LDA.

I. INTRODUCTION

Multibiometric system offer several advantage compare to the unimodal biometric system. In multibiometric system two or more individual biometric modalities are combined together to form a secure and better performance system. Since unimodal biometric system are often affected by several practical problems like noisy senses data, intra-class variation, spoofing attack, non-universality and unacceptable error rate [1]. In order to overcome the problem of unimodal [2] examined the possible performance improvement of biometric by using multiple biometric known as multimodal biometric. The multibiometric system integrates more than one modalities to enhance the performance and accuracy level of the system, so it capable of handling more efficiently the nonuniversality problem of human traits. Fusion of multibiometric traits provides useful information which can be used to distinguish between the genuine and imposter user, so it plays an important role in personal identification purpose. Prevailing practices in multimodal fusion are broadly categorized as prematching (sensor, feature) and pos-matching (score, decision) fusion [3]. The feature set hold richer information about the raw biometric data at feature level than the match or decision level fusion. Feature level fusion is expected to provide better recognition result. However score level fusion and decision level fusion are more popular in the literature and there is not much research on feature level fusion. The main difficulty in feature level fusion is cases where the features are not compatible.e.g eigen-coefficient of face and minutiae sets of fingerprints. The main goal of feature level fusion is to combine the feature set from different sources and combine them into a single one. Two popular feature level fusions are: serial and parallel feature fusion. Serial feature fusion works by simply concatenating two or more feature vector into a single feature vector. Suppose first feature vector of p-dimension and second feature vector of q-dimension then the fused feature vector will be of (p+q) dimension. Parallel feature fusion on the other hand combine the two feature vector into a complex vector z=x+iy (i is imaginary) [4]. The most successful feature level fusion method now a day is CCA (canonical correlation analysis) which uses the correlation between two set of feature to find two sets of transformation such that the transformed feature have maximum correlation across the two features sets [5]. But CCA based feature fusion often suffer from the small sample size problem. The kernel trick (KCCA) is an effective way to solve the small size problem and non-linear problem [6]. The primary objective of this proposed work is to achieve an increased recognition rate with reduced processing time. The goal of the feature fusion for recognition is to combine relevant information from two or more feature vector into a single one which is considered more discriminative than any of the input feature vectors. At feature level fusion, the sets of feature vectors extracted from different modalities are combined together and subsequently used for classification purpose [7]. The advantage of feature level fusion lies in two aspects, it can derive the most discriminatory information from original multiple feature sets involved in fusion; secondly, it is able to eliminate the redundant information or noise from the resultant information. In general, the existing feature fusion technique for pattern classification can be classified as feature selection based and feature extraction based [8]. The remainder of this paper is organized as follow: in section 2 related works are presented; section 3 explain the feature level fusion; section 4 give details about the proposed work; section 5 give details about experimental result and section 6 concludes the papers.

II. Related work

Feature level fusion is expected to provide better recognition result. However score level fusion and decision level fusion are more popular in the literature and there is not much research on feature level fusion. Fusion at this level combine the feature sets from multiple sources. Integration of sources at this level expected to provide better authentication result because the feature set at this level contains richer information about the raw biometric data than the score and decision level. Table 1 show the details of work done in the area of feature level fusion.

Table 1: Multimodal systems based on feature level fusion

S.No	Year	Author	Fusion Level & Type	Traits
01	2015	Yen et al.[9]	Feature, Multi-sample	Palm-vein
02	2015	Derbel et al.[10]	Feature, Multi-modal	Face and gait
03	2015	Xing et al.[11]	Feature, Multi-modal	Face and gait
04	2015	Ahmed et al.[12]	Feature , Multi-modal	Face and palmprint
05	2015	Kanhangard et al.[13]	Feature, Multi-algorithm	Contactless hand geometry
06	2015	Gudavalli et al.[14]	Feature, Multi-algorithm	Fingerprint minutia and ridge
07	2014	Miao et al.[15]	Feature, Multi-modal	Face and eye
08	2013	Huang et al.[16]	Feature, Multi-modal	Face and ear
09	2013	Gawande et al.[17]	Feature, Multi-modal	Fingerprint and iris
10	2013	Guan et al.[18]	Feature, Multi-modal	Face and gait
11	2012	Yang and Zhang[19]	Feature, Multi-modal	Finger and finger-vein
12	2012	Ben et al.[20]	Feature, Multi-modal	Face and gait
13	2012	Long et al.[21]	Feature, Multi-modal	Fingerprint and face
14	2011	Kisku et al.[22]	Feature, Multi-modal	Face and palmprint
15	2010	Guru et al.[23]	Feature, Multi-instance	Finger Knuckle Print

III. Feature level fusion

In this paper we use serial feature level fusion strategy, in which a simple concatenation of the feature sets obtained from multiple information sources. Let $P = \{p_1, p_2, \dots \dots p_m\}$ and $Q = \{q_1, q_2, \dots\dots q_n\}$ denotes feature vectors representing the information extracted from two different sources. After feature level fusion we get a feature vector R of dimension (m+n) whose element is obtained by simply combining the feature sets of P and Q.The following are the different steps in feature level fusion.

A. Feature Normalization

The main goal of feature normalization is to transform the different source of information into a common format prior to fusion process because the individual features values of vectors P and Q may exhibit significant variation both in their range and distribution. The simplest and most popular normalization technique is min-max normalization. Let x'and x denotes the features value after and before normalization process. The min-max normalization technique compute the value of x' as follow:

$$x' = \frac{x - \min\,(F_x)}{\max(x) - \min\,(F_x)} \text{ .... (1)}$$

Where F_x is the function which generate x.
The min-max normalization technique is effective when we have prior information about the maximum and minimum value of the feature vector. In case if such information is not available then we estimate the parameter using the training sample. After the normalization process the resultant set of feature vectors are as follow:

$$p' = \{p_1', p_2', p_3', \dots \dots, p_m'\} \text{ .... (2)}$$
$$Q' = \{q_1', q_2', q_3', \dots \dots, q_n'\} \text{........................(3)}$$

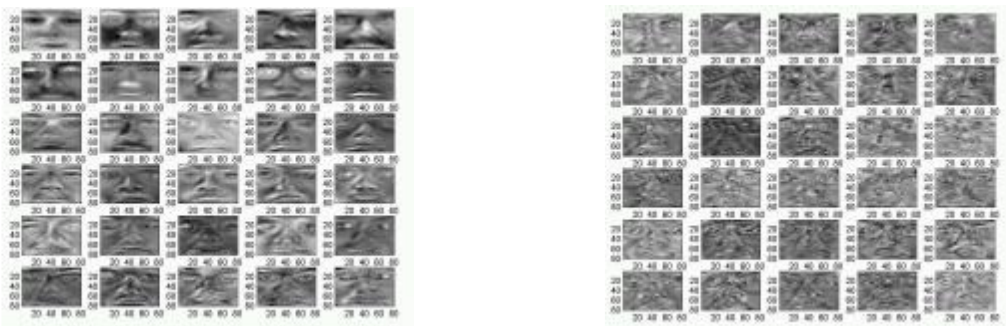
B. Match score generation

Let $\{X_i, Y_i\}$ and $\{X_j, Y_j\}$ be the two feature vector obtained at two time instance i and j.The corresponding fused feature vector may be denoted as Z_i and Z_j, respectively. Suppose s_x and s_y be the normalized match (Euclidean distance) scores generated by comparing x_i with x_j and y_i with y_j.Finally using the simple sum rule the fused match score is calculated as follow:

$$s_{match} = (s_x + s_y)/2 \text{ .... (4)}$$

IV. Proposed work

In this paper we proposed a multibiometric system using feature level fusion of face and hand geometry for personal identification. The Principle Component Analysis (PCA) and Linear Discriminant Analysis (LDA) technique are used for feature extraction of face and each face image was decomposed into its components R, G, B channels. The proposed technique was tested on two different scenarios: (i) fusion of PCA and LDA coefficient of face (ii) fusion of face and hand modalities. Figure 1 shows the image of faces extracted using PCA and LDA technique.



(a) **(b)**

Figure 1: Image of face using (a) PCA (b) LDA technique

The extracted feature from face and hand are fused together by FU (feature unit) model and finally with the help of DM (decision module) it is enabling to decide whether the claimed user is accept or reject.

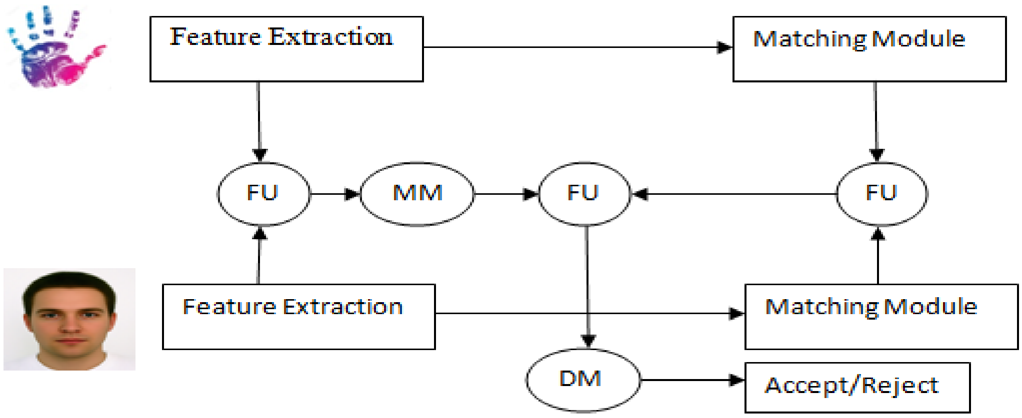


Figure 2: Proposed system using a combination of feature and score level fusion

V. Experimental Result

A set of 450 face image and hand image were collected from 90 users (5 biometric samples per user per biometric).The face images are collected from AR Face Database and hand images acquired from 90 subjects. Five samples are collected in the first session (training samples), followed by another five samples in the second session (probe samples). Hand geometry biometric systems utilize features such as finger length, finger width, finger thickness, finger area, and palm width to perform personal authentication. These systems have gained immense popularity and public acceptance as evident from their extensive deployment for applications in access control, time attendance applications and several other verification tasks. Major advantages of hand geometry systems include simple imaging requirements (features can be extracted from low-resolution hand images), the ability to operate under harsh environmental conditions (immune to dirt on the hand and other external factors), and low data-storage requirements. The proposed technique was tested on three different scenarios (i) fusion of PCA and LDA coefficient and (ii) fusion of face and hand modality.

5.1 Fusion of PCA and LDA Coefficient

The fusion of PCA and LDA coefficient of face is shown in figure 3.It is found that the performance of LDA coefficient of face is outperforming than the PCA coefficient of face. At a FAR (False acceptance rate) =0.01% the GAR (Genuine acceptance rate) is almost 50% and for LDA technique it is almost 80%.The EER(Equal error rate) value is 2.9% in the case of match level fusion and in the case of fusion of feature and match score level it is about 2.51%.

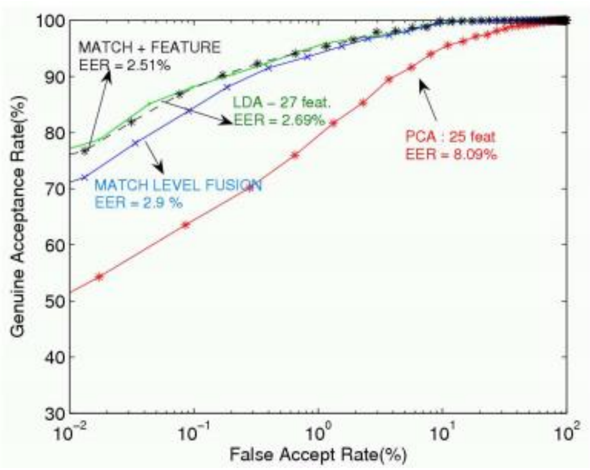


Figure 3: Fusion of PCA and LDA coefficient of face

5.2 Fusion of Face and Hand Biometrics

The 9 byte hand feature set and the LDA-coefficient (27 features) of the face image were combine together to form a fused feature. The performance of the proposed fusion scheme (feature + score) was observed to be superior to that of match score level fusion (Figure 4).

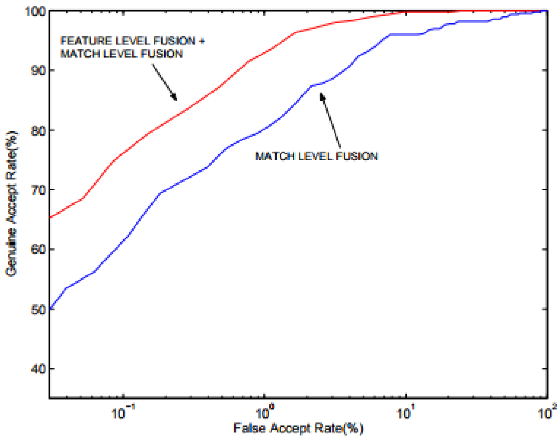


Figure 4: Fusion of face and hand biometrics

Conclusion:

In this paper we propose a multibiometric system for personal identification based on feature level fusion of face and hand. This paper discuss fusion at the feature level at two different scenario, one is fusion of PCA and LDA co-efficient of face and other is fusion of face and hand biometrics. The experiment result shows that the performance of the LDA-based matcher is much higher than that of the PCA-based matcher. The performances of the proposed fusion (feature + score) scheme was observed to be superior to that of match score level fusion. However it is difficult to predict the best fusion strategy given a scenario.

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