Multi-Modal Biometrics Human Verification using LDA and DFB

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Abstract

Biometrics is one of the recent trends in security, which is mainly used for verification and recognition systems. By using biometrics we confirm a particular person's claimed identity based on particular person's physiological or behavioral characteristics such as fingerprint, face or voice etc. This is the extension work of my previous two papers, which tries to overcome the difficulties of single modality. These limitations are addressed by multi-modal biometric verification system as explained in my previous papers. I have chosen existing methodologies like Facial and Finger Print verification modals, ANN to be combined for verification. In this we use Linear Discriminant analysis (LDA) for face recognition and Directional filter bank (DFB) for fingerprint matching. Based on experimental results, the proposed system can reduce FAR down to 0.0000121%, which proves that the proposed method overcomes the limitation of single biometric system and proves stable personal verification in real-time.

Keywords: Biometrics, Multimodal, Face, Fingerprint, Linear Discriminant Analysis, Artificial Neural Network

1.INTRODUCTION

In spite of increased use of computers and the internet in most of the day-to-day activities, traditional person authentication and identity verification methods based on PINs, passwords and tokens have met with limited results. By using biometric traits on the other hand, which involves confirming or denying a person's claimed identity based on his/her physiological or behavioral characteristics, such as person's fingerprint or voice, some of the problems with PIN and password based systems can be addressed [1]. However, all biometric traits do not enjoy the same level of user-acceptance, because of traditional usage of biometrics for criminal identification and anti-terrorism measures. A biometrics is "Automated methods of recognizing an individual based on their unique physical or behavioral characteristics" [1] Human biometric characteristics are unique, so it can hardly be duplicated [2]. Such information include; facial, speech, hands, body, fingerprints, and gesture to name a few.

Biometrics is classified into two groups: passive and active. Passive biometrics recognizes people without their knowledge or cooperation. Examples of these methods comprise of face recognition, odor recognition, and gait recognition. Active biometrics, on the other hand, requires the cooperation of the subject. Examples of these methods include fingerprint authentication, hand graph authentication and iris authentication. Many biometrics are akin in nature but are deployed in different manners. For example, face recognition and face authentication use similar identification algorithms, but the former is a passive biometric and the latter is active.

Face recognition [5], [6], [7] is a form of biometric identification. Face recognition is a vague problem under the conditions of pose, illumination, and database size etc., Still it catches the attention of momentous research efforts. The main reasons for the ongoing research are its many real world applications like human/computer interface, surveillance, authentication, perceptual user interfaces and lack of robust features and classification schemes for face recognition task [8]. Linear Discriminant Analysis (LDA) is a typical and successful face based technique. Turk and Pentland developed a face recognition system using PCA in 1991 [9] [10]. Belhumeur et al. proposed Fisher face technique based on Linear Discriminant Analysis (LDA) in 1997 [11]. At present fingerprints are the most extensively used biometric features for personal recognition. Fingerprint images are direction-oriented patterns created by ridges and valleys. In latest years, fingerprints are mainly used for personal identification. Most automatic systems for fingerprint comparison are based on minutiae matching. The biological properties of fingerprint formation are implicit and fingerprints have been used for recognition purposes for centuries. Various studies have indicated that no single modality can provide a satisfactory solution against impostor attacks. The exploit of multiple modalities such as Face and Fingerprint can conquer the confines of techniques based on a single modality.

In this paper we examine the levels of fusion that are conceivable in a multimodal biometric system, the various scenarios that are doable, the different modes of operation, the integration strategies that can be adopt and the concerns related to the design and exploitation of these systems. The proposed method fuses face recognition and Fingerprint recognition. Though researchers have been started to working on this multi-modal concept, our approach varies from them by different techniques. In this we use the Linear Discriminant Analysis for Face recognition and Directional Filter Bank (DFB) for Fingerprint matching. Thus multi-modal biometric verification method decrease false acceptance rate (FAR), false rejection rate (FRR) and reliability in real-time by overcoming technical limitations of single biometric verification methods

2. FACE RECOGNITION

Face recognition becomes more essential in current years. Numerous face recognition methods have been proposed in last decades. But extrinsic imaging factors such as pose, illumination and facial expression still cause much trouble in precise face recognition. Principle component analysis (PCA) and linear discriminant analysis (LDA) are two powerful tools utilized for data reduction and feature extraction in face recognition approaches [12]. PCA based approaches typically include two phases: training and classification. In the training phase, an eigenspace is established from the training samples using PCA and the training face images are mapped to the eigenspace for classification. In the classification phase, an input face is projected to the same eigenspace and classified by an appropriate classifier. Contrasting the PCA which encodes information in an orthogonal linear space, the linear discriminant analysis (LDA) method (Belhumeur et al., 1997 [13]; Zhao et al., 1998 [14]) which is also known as fisherfaces method is another example of appearance-based techniques which encodes discriminatory information in a linear separable space of which bases are not necessarily orthogonal [15].

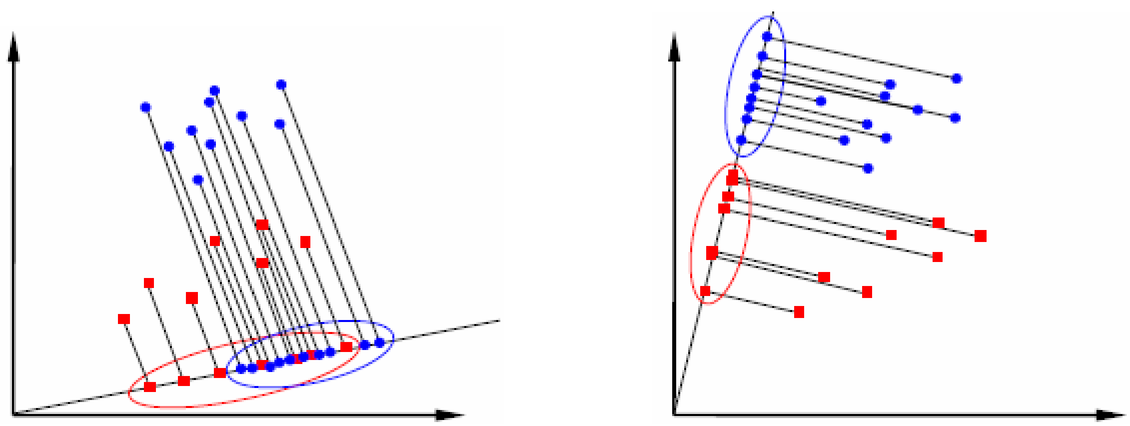
2.1 Linear Discriminant Analysis

Linear Discriminant analysis or Fisherfaces method surmounts the margins of eigenfaces method by applying the Fisher's linear discriminant criterion. This criterion tries to maximize the ratio of the determinant of the between-class scatter matrix of the projected samples to the determinant of the within-class scatter matrix of the projected samples.

Fisher discriminants group images of the similar class and separate images of divergent classes. Images are projected from N2-dimensional space to C dimensional space (where C is the number of classes of images). For example, consider two sets of points in 2-dimensional space that are projected onto a single line. Depending on the direction of the line, the points can either be mixed together (Figure 1a) or separated (Figure 1b). Fisher discriminants find the line that best separates the points. To recognize an input test image, the projected test image is compared to each projected training image, and the test image is recognized as the closest training image.

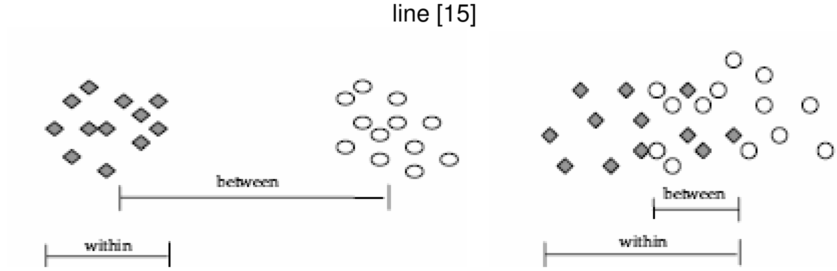
As with eigenspace projection, training images are expected into a subspace. The test images are projected into the same subspace and recognized using a similarity measure. What differs is how the subspace is calculated.

Disparate the PCA method that haul out the features to best represent face images; the LDA method strives to discover the subspace that best discriminates dissimilar face classes as shown in Figure 1. The within-class scatter matrix, also called intra-personal, represents variations in appearance of the same individual due to different lighting and face expression, while the between-class scatter matrix, also called the extra-personal, represents variations in appearance due to a difference in identity. By applying this method, we find the projection directions that on one hand maximize the distance between the face images of different classes on the other hand minimize the distance between the face images of the same class. In another words, maximizing the between-class scatter matrix S_b, while minimizing the within-class scatter matrix S_w in the projective subspace. Figure 2 shows good and bad class separation. [15]



(a) (b)

FIGURE1: (a) Points mixed when projected onto a line. (b) Points separated when projected onto another line [15]



(a) (b)

FIGURE2: (a) Good class separation. (b) Bad class separation [15]

The within-class scatter matrix Sw and the between-class scatter matrix Sb are defined as

$$S_w = \sum_{j=1}^{C} \sum_{i=1}^{N_j} (\Gamma_i^j - \mu_j)(\Gamma_i^j - \mu_j)^T \tag{1}$$

Where $\Gamma_i^{\,j}$ is the i^{th} sample of class j, μ_j is the mean of class j, C is the number of classes, N_j is the number of samples in class j.

$$S_b = \sum_{j=1}^{C} (\mu_j - \mu)(\mu_j - \mu)^T \tag{2}$$

where μ represents the mean of all classes. The subspace for LDA is spanned by a set of vectors $W = [W_1, W_2, \ldots, W_d]$, satisfying

$$W = \arg\max = \left|\frac{W^T S_b W}{W^T S_W W}\right| \quad (3)$$

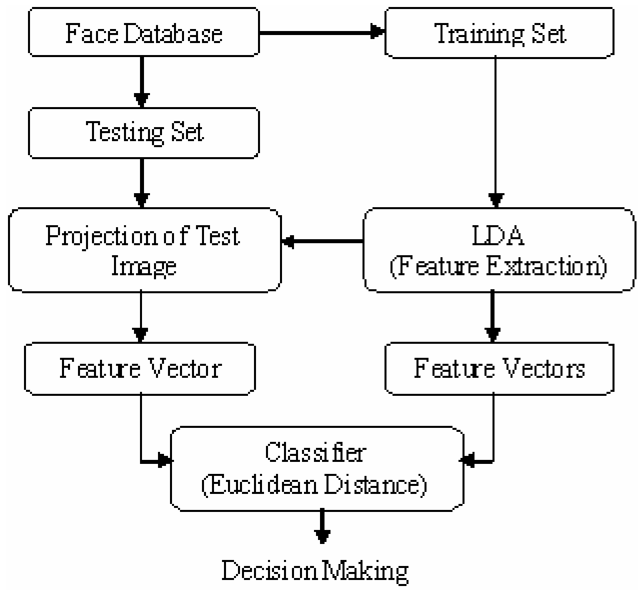


FIGURE3: LDA approach for face recognition

The within class scatter matrix signifies how face images are disseminated closely within classes and between class scatter matrix depicts how classes are alienated from each other. When face images are projected into the discriminant vectors W, face images ought to be distributed closely within classes and should be separated between classes, as much as probable. In other words, these discriminant vectors diminish the denominator and maximize the numerator in Equation (3). W can therefore be constructed by the eigenvectors of S_{w-1} S_b. These eigenvectors are also referred to as the fisherfaces. There are various methods to solve the problem of LDA such as the pseudo inverse method, the subspace method, or the null space method.

The LDA approach is alike to the eigenface technique, which makes use of projection of training images into a subspace. The test images are projected into the same subspace and recognized using a similarity measure. The only variation is the system of calculating the subspace characterizing the face space. The face which has the least distance with the test face image is labelled with the identity of that image. The minimum distance can be calculated using the Euclidian distance method given as $\varepsilon_k = |(\Omega - \Omega_k)|$, Where Ω_k is a vector describing the k^{th} faces class. Figure 3 shows the testing phase of the LDA approach.

3. FINGERPRINT AUTHENTICATION SYSTEM

Fingerprints biometric features are moreover used for personal identification. Fingerprint recognition is one of the basic tasks of the Integrated Automated Fingerprint Identification Service (IAFIS) of the most famous police agencies [16].

MINUTIAE-BASED matching techniques that use minutia points like ridge endings or bifurcations as feature points for verification are the most popular techniques in the field of fingerprint-based biometrics [17], [18], [19], [20]. This is for the reason that minutiae in a fingerprint offers a very dense and discriminatory information. However, these approaches have several demerits. First, it is not easy to take out minutia points automatically and accurately. Second, the number of minutia points available may not be adequate, particularly in systems using small-size fingerprint sensors. In addition, there are also difficulties related to aligning the minutiae patterns from the input and template fingerprints, because the number of minutia points from an input fingerprint generally differs from the number in the template fingerprint.

To overcome or complement the minutiae-based approaches, many image-based techniques that directly extract features from a fingerprint without detecting minutia points have been introduced [21], [22], [23], [24], [25]. The methods moreover calculate the correlation between the input and template fingerprints after certain preprocessing or extract fingerprint features using filtering or transforms and then carry out the matching. These approaches have the benefit that they do not need to haul out minutia points and usually produce a compact fixed-size feature vector. However, they have a tendency to have the difficulty of not properly handling rotational alignment offsets.

Methods for handling rotation misalignments typically involve storing various rotated versions of the template for matching comparison [22]—a strategy which incurs higher complexity and storage costs.

DFB method for fingerprint matching is intense to various rotations and translations of an input fingerprint.

3.1 Directional Filter Bank

The DFB method incorporates directionality as a well-known feature component and represents the fingerprint in terms of directional energies. A reference point is established initially (as we will describe later). The area within a certain radius around the detected reference point is then used as a region of interest (ROI) for feature extraction. Fingerprint features are extracted from the ROI using a directional filter bank (DFB), which efficiently decays the image into numerous directional subband outputs. From the decomposed subband outputs, directional energy values are calculated for each block. The ROI in turn is represented by normalized directional energies in each block. In this representation, only the dominant ones are retained. The rest of the directional energies are set to zero, effectively treating them as noise. As part of the matching process, rotational and translational alignment between the input and template is performed through a normalized Euclidean distance. Please refer [26] for the Detailed attendant to the feature extraction and matching process.

4. ARTIFICIAL NEURAL NETWORK

In this section, the MBP-ANN [29] method will be presented. An ANN is a computer model derived from a simplified concept of the brain [27]. It is a parallel distributed processing system composed of nodes, called neurons, and connections, called weights, and is based on the principle that a highly interconnected system of simple processing elements can learn complex interrelationships between independent and dependent variables. The most popular ANN is the back-propagation ANN (BP-ANN) [28].

4.1 Training Process of MBP-ANN

The BP-based training algorithm of the ANN uses change of weighted value between input layer, hidden layer, and output layer. Fig.4 shows the proposed [29] MBP-ANN. Change of weighted value between input and hidden layers can be expressed as V X x Δ =αδ, and change of weighted value between hidden and output layers as W Z y Δ =αδ, where α represents the learning rate, x δ and y δ represent the error signals of the output of hidden and output layers, respectively. And X, Y, and Z represent the external input, the output of output layer, and the output of hidden layer, respectively. The activation function of method uses the sigmoid function,

$$f(x) = \frac{1-e^{-x}}{1+e^{-x}} \tag{4}$$

The learning rate α initially has a small value because it can decrease with a change of weighted value at the learning step. In this case the learning becomes very slow. The MBP-ANN [29] can accelerate the learning step of BP-ANN. The method utilizes the weighted value of the previous learning step. The learning method of the MBP-ANN algorithm is the same to BP-ANN. But the change of weighted values ΔV and ΔW, only differ from additional momentum expression given in (5). The change ΔVk and k ΔW of weighted value at the k – th learning step of MBP-ANN algorithm is given as:

$$\Delta V_k = \alpha\delta_z X + \beta\Delta V_{k-1},\ \Delta W_k = \alpha\delta_y Z + \beta\Delta W_{k-1}, \tag{5}$$

Where α and β represent the learning rate, and a momentum constant respectively. And z δ and y δ represent the error signal of the hidden and output layer respectively. Therefore, the weighted value k+1 V and k+1 W at the k +1st learning step is given as:

$$\Delta V_{k+1} = V_k + \Delta V_k = V_k + \alpha\delta_z X + \beta\Delta V_{k-1},$$

$$\Delta W_{k+1} = W_k + \Delta W_k = W_k + \alpha\delta_y Z + \beta\Delta W_{k-1}. \tag{6}$$

The square error $E = \frac{1}{2}(d-y)^2$, Computes the target value d and the last output y.

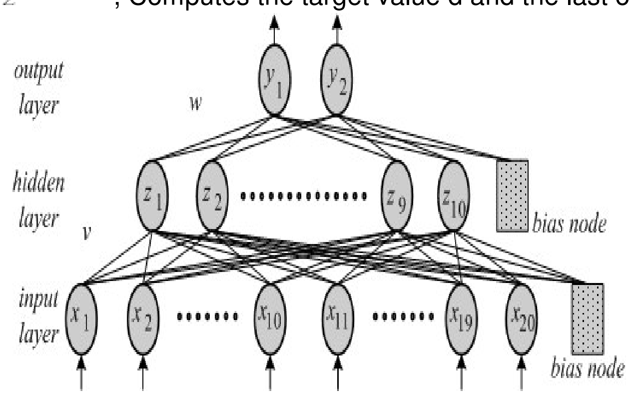


FIGURE4: Momentum back-propagation artificial neural network (MBP-ANN) [29]

5. MULTIMODAL BIOMETRIC PRIORITY VERIFICATION SYSTEM

The multimodal biometric priority verification technique can solve the fundamental limitations inherent to a single biometric verification system. The priority verification system consists of the input, the learning, and the verification modules [29]. The input image of size 300 x 240 comes into the system in real-time together with the fingerprint. In the learning modules, the face image is trained under the Laplacian face, and the fingerprint is trained with DFB. Feature extraction is also accomplished in the learning module. The verification module validates the recognized data from the image and fingerprint by using the MBP-ANN algorithm. Personal information is saved in the form of a codebook class, and is used for verification or rejection [30], [31].

5.1 Personal Verification Using Multimodal Biometric

In this subsection, we present a personal priority verification method shown in Figure: 5. the method first distinguishes the face area from the input image. The face verification module compares the detected face with the pre-stored codebook class of personal information. The fingerprint verification module extracts and recognizes the endpoint of fingerprint, and confirms it after comparing with the codebook class. Decision processes of face and fingerprint use the MBP-ANN algorithm. If the face and fingerprint verification results match, then there is in no further processing.

Otherwise the MBP-ANN is used to solve the mismatch problem. Therefore, if the face and fingerprint is the same to the personal information of the codebook class, verification is accepted. Otherwise, it is rejected. The entire priority verification process is shown in Figure: 5.

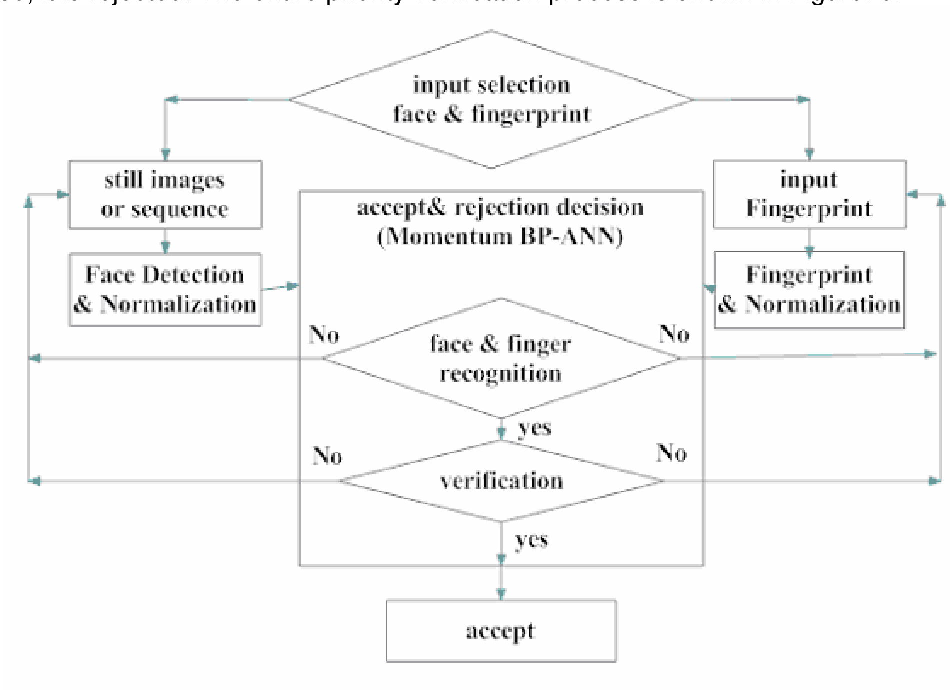


FIGURE5: The entire priority verification process [29]

6. EXPERIMENTAL RESULTS

The experimental result for the verification rate using the proposed method is summarized in Table 1, which shows the result of the verification rate and FAR obtained by the proposed method. As shown in Table 1, the proposed method can reduce FAR to down 0.0000121%, and the impersonation to one person out of 1,000.

Images	Genuine Acceptance Rate (%)	FAR (%)
Face & Palmprint	99.9789	0.0000121

TABLE1: Verification rate of the proposed method

7. CONCLUSION

This paper is an extension of my two previous works; a priority verification method for multi-modal biometric features by using the MBP-ANN, which improves the limitation of single biometric verification, which has the fundamental problems of high FAR and FRR. In this paper we have discussed the multimodal biometric priority verification technique which can solve the fundamental limitations inherent to a single biometric verification system. The verification module validates the recognized data from the face image and fingerprint by using the MBP-ANN algorithm. In that we adopted the Linear Discriminant analysis for face recognition and Directional filter Bank for fingerprint recognition for real-time personal verification. Based on the experimental results we show that the FAR reduce to 0.0000121% in the human multimodal verification system. As a result the proposed priority verification method can provide stable verification rate, and at the same time it overcomes the limitation of a single-mode system.

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