Bizarre Approaches For Multimodal Biometrics

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Summary
Establishing the identity of a person is becoming critical in our vastly interconnected society. Most biometric systems deployed in real-world applications are unimodal. i.e., they rely on the evidence of a single source of information. These limitations are addressed by multimodal biometric verification system as explained in this paper. We have selected. A multi-modal biometric system generally means the multiple biometrics system. We have chosen existing methodologies like Facial and Finger Print verification modals, ANN to be combined for verification. As a result, the performance of the proposed approach outperforms that of a single modal by about four times. Based on experimental results, the proposed system can reduce FAR down to 0.000111%, which proves that the proposed method overcomes the limitation of single biometric system and proves stable personal verification in real-time.

Key words:
Multimodal, Biometric System, Face Recognition, Locality, Verification.

1. Introduction

Human biometric characteristics are unique, so it can hardly be duplicated [30-][1]. These systems rely on the evidence of fingerprints, hand geometry, iris, retina, face, hand vein, facial thermogram, signature, voice, etc. to either validate or determine an identity [2].

Most biometric systems deployed in real-world applications are unimodal, i.e., they rely on the evidence of a single source of information for authentication. These systems have to contend with a variety of problems[31] such as: (a) Noise in sensed data: A fingerprint image with a scar, or a voice sample altered by cold are examples of noisy data. Noisy data could also result from defective or improperly maintained sensors (e.g., accumulation of dirt on a fingerprint sensor) or unfavorable ambient conditions (e.g., poor illumination of a user's face in a face recognition system). (b) Intra-class variations: These variations are typically caused by a user who is incorrectly interacting with the sensor (e.g., incorrect facial pose), or when the characteristics of a sensor are modified during authentication (e.g., optical versus solid-state fingerprint sensors). (c) Inter-class similarities: In a biometric system comprising of a large number of users, there may be inter-class similarities (overlap) in the feature space of multiple users. Golfarelli et al. [3] state that the number of distinguishable patterns in two of the most commonly used representations of hand geometry and face are only of the order of 105 and 103, respectively. (d) Non-universality: The biometric system may not be able to acquire meaningful biometric data from a subset of users. A fingerprint biometric system, for example, may extract incorrect minutiae features from the fingerprints of certain individuals, due to the poor quality of the ridges. (e) Spoof attacks: This type of attack is especially relevant when behavioral traits such as signature or voice are used. However, physical traits such as fingerprints are also susceptible to spoof attacks. Some of the limitations imposed by unimodal biometric systems can be overcome by including multiple sources of information for establishing identity [5]. Such systems, known as multimodal biometric systems, are expected to be more reliable due to the presence of multiple, (fairly) independent pieces of evidence [6]. These systems are able to meet the stringent performance requirements imposed by various applications. They address the problem of non-universality, since multiple traits ensure sufficient population coverage. They also deter spoofing since it would be difficult for an impostor to spoof multiple biometric traits of a genuine user simultaneously. Furthermore, they can facilitate a challenge response type of mechanism by requesting the user to present a random subset of biometric traits thereby ensuring that a 'live' user is indeed present at the point of data acquisition. In this paper we examine the levels of fusion that are plausible in a multimodal biometric system, the various scenarios that are possible, the different modes of operation, the integration strategies that can be adopted and the issues related to the design and deployment of these systems.

Our proposed multimodal biometric method is to improve both verification rate and reliability in real-time by overcoming technical limitations of single biometric verification methods. The proposed method fuses face recognition and Fingerprint recognition. Though researchers have started working on this multimodal, our approach varies from them by the different techniques chosen like Laplacianface approach [12] for Facial recognition and Directional Filter Bank (DFB) for Fingerprint fingerprint matching [27] and Artificial NeuralNetwork[30] For training and testing.. Section 6

Manuscript received July 5, 2008.
Manuscript revised July 20, 2008.

presents experimental results, and Section 7 concludes the paper with future research topics.

2. Laplacianface

2.1 Facial Recognition

Face detection and recognition techniques are proven to be more popular than other biometric features based on efficiency and convenience [7], [8]. It can also use a low-cost personal computer (PC) camera instead of expensive equipments, and require minimal user interface.

There have been many approaches to extracting meaningful features for the recognition purpose. Those include principal component analysis (PCA) [9], neural networks (NN) [9], hidden markov models (HMM) [10], and linear discriminant analysis (LDA) [11]. Laplacianface approach [12] is significantly outperforms both Eigenfaces and Fisherfaces methods.

2.2 Locality Preserving Projection

PCA and LDA aim to preserve the global structure. However, in many real world applications, the local structure is more important. In this section, we describe Locality Preserving Projection (LPP) [13],a new algorithm for learning a locality preserving subspace. Each face image in the image space is mapped to a low dimensional face subspace, which is characterized by a set of feature images, called Laplacianfaces. he complete derivation and theoretical justifications of LPP can be traced back to [13]. LPP seeks to preserve the intrinsic geometry of the data and local structure. The objective function of LPP is as follows:

$$\min \sum_{ij} (y_i - y_j)^2 S_{ij} \tag{1}$$

where is the one-dimensional representation of and the matrix S is a similarity matrix. A possible way of defining S is as follows:

This paper is organized as follows: Sections 2 and 3 describe feature extraction of face and Fingerprint using the Laplacianface and Directional Filer Bank algorithms, respectively. Sections 4 and 5 present the theory artificial neural network (ANN) and how to design the structure of the proposed system,

$$S_{ij} = \begin{cases} \exp(\|\mathbf{x}_i - \mathbf{x}_j\|^2 / t), & \|\mathbf{x}_i - \mathbf{x}_j\|^2 < \varepsilon \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

Or

$$S_{ij} = \begin{cases} \exp(\|\mathbf{x}_i - \mathbf{x}_j\|^2 / t), & \text{if } \mathbf{x}_i \text{ is among } k \text{ nearest neighbors of } \mathbf{x}_j \\ & \text{or } \mathbf{x}_j \text{ is among } k \text{ nearest neighbors of } \mathbf{x}_i \\ 0 & \text{otherwise.} \end{cases}$$

where ε is sufficiently small, and ε > 0. Here, ε defines the radius of the local neighborhood. In other words, ε defines the "locality". The objective function with our choice of symmetric weights Sij (Sij = Sji) incurs a heavy penalty if neighboring points xi and xj are mapped far apart, i.e. if (yi − yj)2 is large. Therefore, minimizing it is an attempt to ensure that if xi and xj are "close" then yi and yj are close as well. Following some simple algebraic steps, we see that

$$\begin{aligned}
&\frac{1}{2}\sum_{ij}(y_i - y_j)^2 S_{ij} \\
&= \frac{1}{2}\sum_{ij}(\mathbf{w}^T\mathbf{x}_i - \mathbf{w}^T\mathbf{x}_j)^2 S_{ij} \\
&= \sum_{ij}\mathbf{w}^T\mathbf{x}_i S_{ij}\mathbf{x}_i^T\mathbf{w} - \sum_{ij}\mathbf{w}^T\mathbf{x}_i S_{ij}\mathbf{x}_j^T\mathbf{w} \\
&= \sum_i \mathbf{w}^T\mathbf{x}_i D_{ii}\mathbf{x}_i^T\mathbf{w} - \mathbf{w}^T XSX^T\mathbf{w} \\
&= \mathbf{w}^T XDX^T\mathbf{w} - \mathbf{w}^T XSX^T\mathbf{w} \\
&= \mathbf{w}^T X(D-S)X^T\mathbf{w} \\
&= \mathbf{w}^T XLX^T\mathbf{w}
\end{aligned}$$

where X = [x1, x2, …, xn], and D is a diagonal matrix; its entries are column (or row, since S is symmetric) sums of S, Dii = Σj Sji. L = D – S is the Laplacian matrix [6]. Matrix D provides a natural measure on the data points. The bigger the value Dii (corresponding to yi) is, the more "important" is yi. Therefore, we impose a constraint as follows:

$$\begin{aligned}
&\mathbf{y}^T D\mathbf{y} = 1 \\
\Rightarrow\ &\mathbf{w}^T XDX^T\mathbf{w} = 1
\end{aligned}$$

Finally, the minimization problem reduces to finding:

$$\underset{\substack{\mathbf{w} \\ \mathbf{w}^T XDX^T\mathbf{w}=1}}{\arg\min}\ \mathbf{w}^T XLX^T\mathbf{w} \tag{3}$$

The transformation vector w that minimizes the objective function is given by the minimum eigenvalue solution to the generalized eigenvalue problem:

$$XLX^T\mathbf{w} = \lambda XDX^T\mathbf{w} \tag{4}$$

Note that the two matrices XLX^T and XDX^T are both symmetric and positive semi-definite, since the Laplacian matrix L and the diagonal matrix D are both symmetric and positive semi-definite.The Laplacian matrix for finite graph is analogous to the Laplace Beltrami operator on compact Riemannian manifolds. While the Laplace Beltrami operator for a manifold is generated by the Riemannian metric, for a graph it comes from the adjacency relation. Belkin and Niyogi [16] showed that the optimal map preserving locality can be found by solving the following optimization problem on the manifold:

$$\min_{\|f\|_{L^2(M)}=1} \int_M \|\nabla f\|^2 \quad (5)$$

which is equivalent to

$$\min_{\|f\|_{L^2(M)}=1} \int_M \mathcal{L}(f) f \quad (6)$$

where L is the Laplace Beltrami operator on the manifold, i.e. $\mathcal{L}(f) = -\operatorname{div}\nabla(f)$.Thus, the optimal f has to be an eigenfunction of L. If we assume f to be linear, we have $f(\mathbf{x}) = \mathbf{w}^T\mathbf{x}$. By spectral graph theory, the integral can be discretely approximated by $\mathbf{w}^T XLX^T \mathbf{w}$ and the L2 norm of f can be discretely approximated by $\mathbf{w}^T XDX^T \mathbf{w}$., which will ultimately lead to the following eigenvalue problem:

$$XLX^T\mathbf{w} = \lambda XDX^T\mathbf{w} \quad (7)$$

The derivation reflects the intrinsic geometric structure of the manifold.

3. Fingerprint

Fingerprints biometric features are also most widely 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 [17].

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 [18]–[21]. This is because minutiae in a fingerprint provide very compact and discriminatory information. However, these approaches have several disadvantages. First, it is not easy to extract minutia points automatically and accurately. Second, the number of minutia points available may not be sufficient, especially 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 [22]–[26]. The methods either compute the correlation between the input and template fingerprints after certain preprocessing or extract fingerprint features using filtering or transforms and then perform matching. These approaches have the advantage that they do not need to extract minutia points and usually generate a compact fixed-size feature vector. However, they tend to have the problem of not properly handling rotational alignment offsets.

Methods for handling rotation misalignments typically involve storing various rotated versions of the template for matching comparison [23]—a strategy which incurs higher complexity and storage costs.

DFB method for fingerprint matching is robust to diverse rotations and translations of an input fingerprint.

3.1 Directional Filter Bank

The DFB method incorporates directionality as a prominent 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 effectively decomposes the image into several 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 [27] for the Detailed attendant to the feature extraction and matching process.

4. Artificial Neural Network

In this section, the MBP-ANN[30] method will be presented. An ANN is a computer model derived from a simplified concept of the brain [28]. 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) [29].

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.1 shows the proposed[30] 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,

$$f(x) = \frac{1-e^{-x}}{1+e^{-x}} \tag{8}$$

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[30] 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 (6). The change ΔVk and k ΔW of weighted value at the k − th learning step of MBP-ANN algorithm is given as:

$$\Delta V_k = \alpha\delta_z X + \beta\Delta V_{k-1},\ \Delta W_k = \alpha\delta_y Z + \beta\Delta W_{k-1}, \tag{9}$$

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:

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

$$\Delta W_{k+1} = W_k + \Delta W_k = W_k + \alpha\delta_y Z + \beta\Delta W_{k-1}, \tag{10}$$

The square error

$$E = \frac{1}{2}(d-y)^2$$

Computes the target value d and the last output y

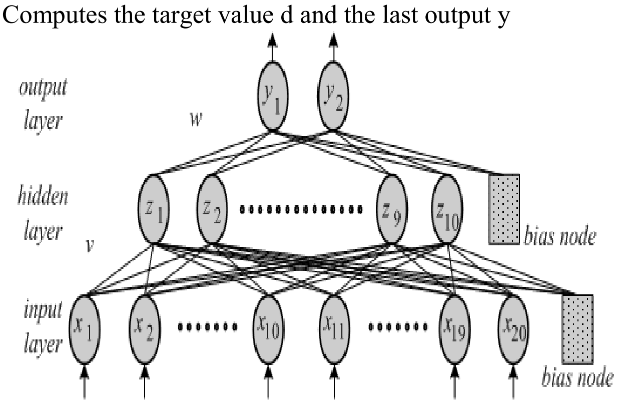

Fig. 1 Momentum back-propagation artificial neural network (MBP-ANN) [30]

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.[30] 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 Laplacianface, 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 used for verification or rejection.

5.1 Personal Verification Using Multimodal Biometric

In this subsection, we present a personal priority verification method shown in Fig. 2. The method first detects 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 authenticates 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 coincide, there in no further processing.

Otherwise the MBP-ANN is used to solve the mismatch problem. Therefore, if the face and fingerprint is same to the personal information of the codebook class, verification is accepted. Otherwise, it is rejected. The entire priority verification process is shown in Fig 2.

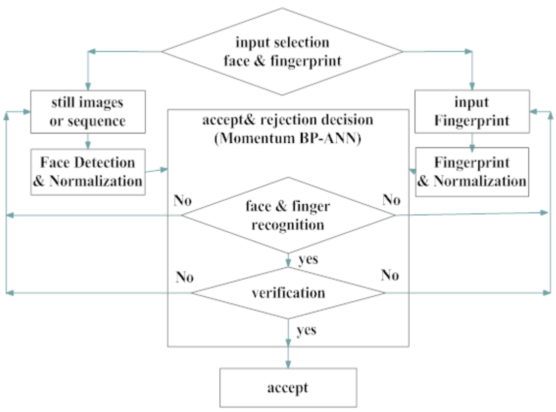

Fig. 2 The entire priority verification process [30]

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 0.0001%, and the impersonation to one person out of 1,000.

Table 1. Verification rate of the proposed method

Images	**Genuine Acceptance Rate (%)**	**FAR (%)**
face & fingerprint	99.999	0.000111

7. Conclusions

In this paper, we proposed a priority verification method for multi-modal biometric features by using the MBP-ANN. We also proposed a human verification method using combined face and fingerprint information in order to improve the limitation of single biometric verification, which has the fundamental problems of high FAR and FRR. The proposed multimodal, biometric priority verification method improves the verification rate and reliability in real-time. We adopted the Laplacianface for face recognition and DFB for fingerprint recognition for real-time personal verification. As a result the proposed priority verification method can provides stable verification rate, and at the same time it overcomes the limitation of a single-mode system. Based on the experimental results, we show that FAR can be reduced down to 0.0001% in the human multimodal interface method using both face and fingerprint information.

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