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Secure Multimodal Biometric Authentication System using Face and Fingerprint Modalities

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***Abstract* - This paper proposes a biometric authentication system based on feature level fusion of face and fingerprint modalities. The proposed method utilizes Gabor filter bank with two scales and eight orientations, to extract directional features from source data. Usage of a small set of Gabor filters typically reduces the system processing time. To introduce a good discriminating ability and to avoid curse of dimensionality in feature set, we have used Principal Component Analysis (PCA) +Linear Discriminant Analysis (LDA) framework. The framework enables us to use only 39 features as input to classifier stage of the system. We have employed distance classifiers to authenticate a person based on the distance between input image and stored database templates. Experimental results showcase the advantages of feature level fusion over a uni-modal framework. The system achieves recognition accuracy up to 99.25%. The experiments have been carried out on ORL face database and FVC2002 fingerprint database.**

Keywords: *feature level fusion, Gabor filter bank, PCA, LDA*

I. INTRODUCTION

For various reasons like security threats, spoof attacks the area of authentication has got a lot of attention from research community. The demand for practical and reliable authentication systems with easy access is ever growing. Traditional authentication systems such as token based access, ID cards or passwords do not provide a good discrimination between fake users and authenticate users. Biometric traits can act as a remedy to this problem as these cues cannot be shared or spoofed easily and every person has uniquely discriminating biometric properties. Biometric modalities are attributed to physiological or behavioral characteristics of a person. Currently used biometric traits can be accounted as face, fingerprint, palm print, iris etc. These biometric have own tradeoffs in terms of recognition performance and user acceptance. However, the performance of a biometric system is dynamic because of presence of noise and distortions in input signal, variations in background conditions and acquisition devices. For example, face recognition systems are heavily suffered due to slight changes in illumination. Iris recognition systems performance degrades due to occlusion of eyelids. Also a uni-modal biometric system can suffer spoof attacks easily.

Researchers have proposed multimodal biometric systems, with better results as a solution to above mentioned disadvantages with uni-modal biometric systems. A typical multimodal system utilizes two or more biometric traits in order to meet stringent performance requirements. Using the idea of integration of multiple cues, some of the limitations of unimodal systems can be improved. And it is difficult to forge multiple traits at a time. So multimodal systems are more close to real time working systems. These systems integrate information at different stages such as feature level, score level, decision level etc. A. Rattani et al [1] proposed a feature level fusion of face and fingerprint biometric modalities and highlight the improvement in results for feature level fusion over the score level one. Chuon-Hong Jiang et al. [2] have presented the fusion of face and fingerprint modalities using similarity scores generated, with help of different classifiers techniques like SVM, FLDA.

This paper presents a multimodal biometric system based on feature level fusion of face and fingerprint modalities. These modalities offer advantages of wide user acceptance, easy accessibility and uniqueness among the users. Fingerprints provide extremely high recognition accuracies due to their uniqueness and face is commonly used by human perceptual systems for person identification. The system utilizes Gabor wavelet filters to extract directional features of the biometric modalities [6] [8] [10] [11]. Further feature sets from both cues are normalized to a standard range of values as they are generated from heterogeneous sources. Further dimensionality reduction techniques are used to avoid curse of dimensionality.

The remainder of the paper is organized as follows. The techniques of Gabor filter bank, Principal Component Analysis and Linear Discriminant Analysis are revisited in section II and III respectively. Section IV describes proposed methodology for face and fingerprint traits. Section V summarizes the results and their analysis regarding to proposed system. Finally, section VI is dedicated to conclude the topic with inferred remarks.

II. GABOR WAVELET THEORY

Gabor wavelets are well known for their effective extraction of local features of image. Gabor filters exhibit the salient properties such as spatial localization, orientation selectivity and spatial-frequency selectivity .Therefore, Gabor filter have been applied to many fields, such as texture classification, face recognition, handwritten character recognition, fingerprint classification and recognition. The feature extraction using Gabor wavelet filters involves the process of convolution of Gabor filter bank at different orientations and scales with input modality image. This yields a high dimensional feature space. The Gabor wavelet kernel is defined as follows:

$$\Psi_{\mu,v}(z) = \|k_{\mu,v}\| exp\left(-\frac{k_{\mu,v}{}^{2}z^{2}}{2\sigma^{2}}\right)\left(\exp(ik_{\mu,v}z)-\exp\left(-\frac{\sigma^{2}}{2}\right)\right) \quad (1)$$

where μ and v in equation 1 define the orientation and scale of the Gabor kernels. The wave vector $k_{\mu v}$ is defined as

$$k_{\mu,v} = k_{v}\exp(i\phi v)$$

where

$$k_v = {k_{max}}/{f} \qquad and \qquad \phi = \pi\mu/8$$

k_{max} is maximum frequency and f is the spacing factor between kernels in the frequency domain. Gabor wavelet representation of an image is given as:

$$O_{\mu,v}(z) = I(z) * \Psi_{\mu,v}(z) \qquad (2)$$

$O_{\mu,v}$ is convolution result corresponding to Gabor kernel at μ orientation and v scale.

Fig 1. Sample Face Database Image.

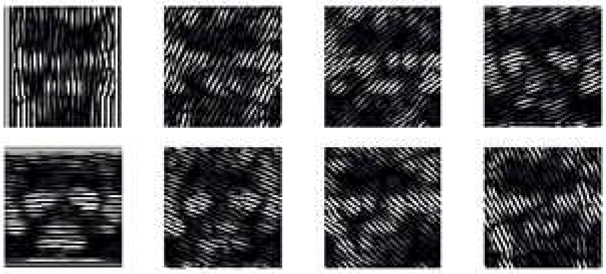

Fig 2. Real part of convolution of the sample face image for single scale.

As convolution of Gabor kernels with database images at μ orientations and v scales generates a high dimensional feature space, we down sample the feature vector by factor of 64. Figure 1 shows sample image from face database and fig. 2 presents convolution output of the sample image with Gabor kernels at single scale and 8 orientations.

III. DIMENSIONALITY REDUCTION TECHNIQUES

A) Principal Component Analysis:

Principal Component Analysis (PCA) is a widely used technique which has been used for dimensionality reduction and recognition purposes. The PCA algorithm reduces the large dimensional data to smaller set of orthogonal (independent) components, exploiting the correlation present in sample data space [12] [13]. Orthogonal components are derived using Eigen vectors of the covariance matrix of input data space. Eigen faces algorithm retains only most significant Eigen vectors and projects input data on Eigen space.

B) Linear Discriminant Analysis:

Linear Discriminant Analysis (LDA) projects images to a lower dimensional space while it attempts to keep images from same class as close as possible, and images from different subjects as separated as possible. Instead of a single covariance matrix, LDA considers within-class scatter matrix S_w and between-class scatter matrix S_b. LDA finds a projection A that maximizes the ratio between S_w and S_b. Here, the eigen vectors of LDA are called Fisher faces. The performance of LDA algorithm depends upon number of samples m, number of classes c, and original space dimensionality d. We require at least d+c samples to have a non-singular S_w.

In proposed work, we have used PCA+LDA structure, which ensures non-singular matrix S_w. Also, this framework facilitates lower dimensional feature space with good discrimination between different classes [9].

IV. PROPOSED METHOD

Figure 3 shows the block diagram for the proposed system. The proposed system is evaluated in terms of recognition accuracies using ORL face database and FVC2002 database for fingerprint modality. ORL face database consists of 40 subjects, with 10 images per subject which exhibit variations in terms of illumination, pose and facial expressions. The images are stored at a resolution 92x112 and 8-bit grey levels. Out of these 400 images 80(2 from each class) images were considered for training and other 80 images were considered for testing purpose. FVC2002 has four databases: DB1, DB2, DB3 and DB4. Each database consists of 800 fingerprint images in 256 gray levels. From DB1 database, we have used 2 images for training as well as for testing purpose for 40 subjects in total.

The Gabor kernel defined in Eq. 1 uses 2 scales and 8 orientations which results in 16 different filters. The input image is convoluted with Gabor filter set. This convoluted Gabor feature set is then down sampled by a factor of 64. Each Gabor feature set generated after convolution of image with different Gabor kernels is concatenated to the end.

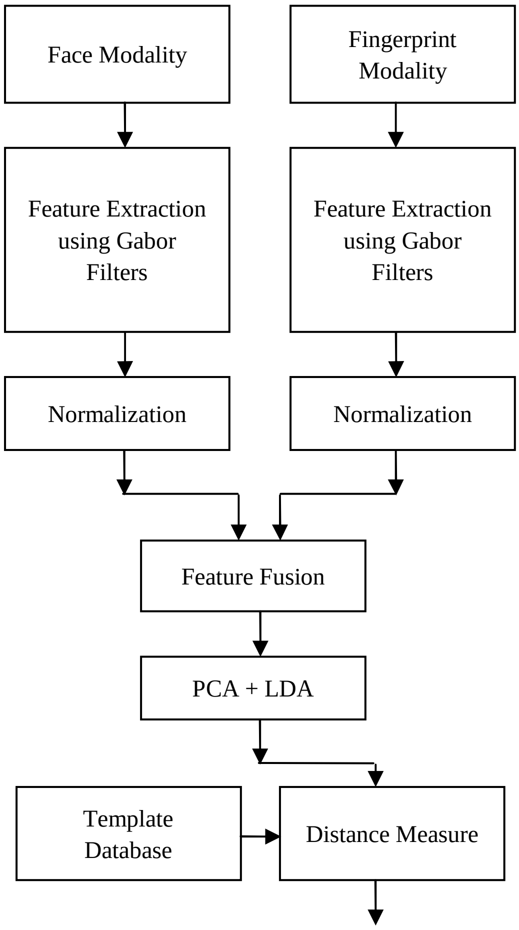

Fig. 3. Block Diagram of Proposed System.

The resulting high dimensional Gabor feature set is used as input to next stage. This stage uses PCA algorithm for reducing the dimensions of Gabor feature set. Here, PCA computes Eigen vectors of a covariance matrix which are then arranged in descending order. Of the total Eigen vectors calculated, top Eigen vectors are retained. The maximum number of Eigen vectors retained is equal to {rank(C)-1}, where C is covariance matrix. To facilitate dimensionality reduction scheme, input matrix is then projected onto Eigen space. The projected Eigen space matrix acts as an input to next stage. The next stage incorporates LDA algorithm to enhance between class separability and further reduction in input dimension. Using projected matrix in PCA stage, LDA calculates within-class scatter matrix.

For fusion strategy of face and fingerprint modalities, feature sets generated from individual cues are normalized using min-max normalization technique. Min-max normalization maps the feature set within range 0 to 1. The distance classifiers are employed to facilitate the matching between the training and testing images. We have mentioned the results for Hellinger distance (D1) and Canberra distance (D2).

Hellinger Distance: In this distance square root of sum of squared square root difference at each dimension is taken which minimizes the difference if similarity between vectors is more.

$$d(x,y)=\sqrt{2\sum_{j=1}^{N}\left(\sqrt{x_j}-\sqrt{y_i}\right)^2} \qquad (3)$$

Canberra distance: The Canberra metric is similar to the Manhattan distance. The distinction is that the absolute difference between the variables of the two objects is divided by the sum of the absolute variable values prior to summing.

$$d(x,y)=\sum_{j=1}^{N}\frac{|x_j-y_i|}{|x_j|+|y_i|} \qquad (4)$$

where,
x_j = testing feature vector
y_i = training feature vector
N = total number of features

V. EXPERIMENTAL RESULTS

Table 1. Results

Modality	FAR (%)		FRR (%)		GAR (%)	
	D1	D2	D1	D2	D1	D2
Fingerprint	1.762	2.2	2.5	2.9	97.5	97.1
Face	13.55	1.6	13.75	11	86.25	89
Fusion of Face and Fingerprint	0.35	0.22	0.75	1.1	99.25	98.90

Table 1 displays experimental results for recognition with face modality alone, fingerprint modality alone and recognition with feature level fusion of face and fingerprint. The results are expressed in terms of False acceptance rate (FAR), False rejection rate (FRR), and Genuine acceptance rate (GAR). Application of Gabor filter bank with two scales over a face definitely collects less information, as it may not account for detailed directional content in the source. So FAR value reaches to 13.55% and FRR to 13.75% with Hellinger distance. However, FAR and FRR values for fingerprint modalities are 1.76% and 2.5% respectively. With fusion of Gabor features for face and fingerprints at feature level, reduces down the values for both FAR and FRR to 0.35% and 0.75% respectively in case of proposed system. The GAR for proposed system reaches to 99.25% consequently.

VI. CONCLUSION

We have presented the feature level fusion scenario in case of face and fingerprint modalities, using Gabor filter bank to extract the features individually. Comparison of individual recognition accuracies for face and fingerprint highlights the robustness of fingerprints. In case of fusion strategy improvement in recognition accuracies can be inferred from results. Integration of information at an earlier stage and its segregation in separate classes using Linear Discriminant Analysis leads to the betterment in results over uni-modal systems proposed. The dimensionality reduction techniques used here like PCA and LDA also help in reducing the inherently involved computational complexity in feature level fusion process. Proposed feature level fusion framework with reduced FAR values ensures an authentication system more secure and immune to spoof attack compared to uni-modal authentication systems.

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