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PCA and DWT Based Multimodal Biometric System for Recognizing a Person Using Face, Ear and Finger

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Abstract - This paper proposes the noble multimodal biometric system using multiple biometric traits such as face, ear and finger. This combination of multimodal traits is unique combination offering a better authenticity and accuracy than the existing multimodal biometric systems. In this experimentation the discrete wavelet transforms (DWT) is used for extraction of features which is followed by the principle component analysis (PCA). The wavelet coefficients are being extracted with the help of different wavelets, where only approximation coefficients are being considered in this experimentation. PCA offers dimension reduction by generating the principle components in the form of eigen faces which is used further for recognition followed by the classification.

Keywords - *Multimodal Biometric System, DWT, PCA, Fusion at Decision Level etc.*

1. Introduction

The biometric recognition system is used for recognizing the person by using either physiological or behavioral features of the persons. Biometric system uses different physiological traits such as face, finger, iris, palm, gait etc. for recognizing the person as genuine or imposter in order to secure the system. The biometric recognition systems are of two different types such as, Unimodal biometric system and Multimodal biometric system. When only one biometric trait is used for recognition purpose then that biometric system is termed as Unimodal Biometric System. On the other hand for increasing the accuracy and secrecy of the system, when more than one i.e. multiple biometric traits are used for recognition then that biometric system is Multimodal Biometric System which is discussed in this paper. It is found that the unimodal biometric system is suffered with some serious limitations because of which it's performance and efficiency of the recognition is affected severely [1]. In certain situations, user might find that, use of only one form of biometric identification is not exact enough for identification. Hence the unimodal biometric system is found to be having the following limitations,

1) Susceptibility of biometric sensors to noise. Which in turn can be lead to inaccurate matching, as noisy data may lead to a false rejection,
2) Incompatibility with certain persons. Elderly people and young children may have difficulty enrolling in a fingerprinting system, due to their faded prints or under developed fingerprint ridges,
3) Spoof attacks, i.e. where the data can be copied or duplicated.
4) Intra-class variations etc.

Hence the unimodal biometric system is replaced by the multimodal biometric systems. In some of the situations multimodality offers an alternative, where a person cannot be recognized because of the precise biometric trait at hand (e.g. a damaged digit in fingerprint verification or a veiled woman in face verification) is not available [2]. It is also more difficult to forge several systems, linked on different traits of the person than a single one and therefore multimodal systems should be more robust against forgeries. Finally, an improvement of performance is also expected through the use of non-correlated biometric modalities.Our approach in this work describes the possible combinations of the biometric traits to improve the accuracy and robustness of the system. In this experimentation the three biometric traits used are face, ear and finger. From this the multiple combinations used for implementing a better biometric recognition system are face and ear, face and finger and the most accurate, robust and authentic combination is face, ear, and finger for recognizing the person by increasing the authenticity considerably. The multimodal biometric system is comprises of the fusion of various biometric modality data.

In a multimodal biometric system using multiple biometric traits, fusion can take place at four different levels of information [3-4], and these levels correspond to four important components of a biometric system as (1) Sensor module, (2) Feature extraction module, (3) Matching module, and (4) Decision-making module. In this work the fusion is done at decision level.

The database used here, is self-created database which consists of the uniform dimensional facial images taken in different illuminations of the light with different moods in different orientations, images of ear and finger prints. Here each class consists of the nine images of face, two images of ear (left ear and right ear) of each person and thumb impressions of the persons. Then, the system will undergo the feature extraction of the preprocessed input images of face and ears. Then in order to recognize the person to be authentic or imposter one, the principle component analysis (PCA) is applied, and is followed by the minimum distance classifier.

The rest of the paper is organized as follows: section II provides detailed explanation of the discrete wavelet transform used for the feature extraction. This feature extraction section is followed by Section III which is comprises of the brief working of the PCA i.e. principle component analysis. Which include the details of covariance matrix, eigenvectors and eigen faces. Next to it, the Section IV gives brief idea about proposed system. The succeeding section V gives the experimental results and analysis of these this experimentation. Finally, conclusions of this study are given in Section VI.

2. Feature Extraction Using Wavelets

This section explains about the feature extraction step in the algorithm of multimodal biometric system proposed in this experimentation. The preprocessed set of the training images is considered for extracting the features. The aim of feature extraction of a preprocessed image is being carried out for representing the image in its most compact and unique form of feature vectors [5].

Wavelet is now more popular tool in image processing and computer vision. The main reasons for Wavelet transforms popularity lies in its complete theoretical framework. The wavelet transform provides an appropriate foundation for image handling because of its valuable features. The few features of the wavelet transform are listed as follows:

1. Energy compaction: Wavelet transform is having the ability to compact most of the signal's energy into a few transformation coefficients.

2. The wavelet transform is capable to capture and represent effectively low frequency components (such as image backgrounds) and the high frequency transients (such as image edges).

Thus wavelet transform concentrates the energy of the image signals into a small number of wavelet coefficients. Hence for extraction of features from images we can use different wavelets explained in following section of this paper. When DWT is applied on the images then, it produces different coefficients; such as approximation coefficient, horizontal coefficient, diagonal coefficient and vertical coefficient. Out of these four different coefficients only the approximation coefficients are being extracted in this experimentation.

2.1 'Haar' Wavelet

Alfred Haar had discovered these Haar sequence in 1909. Haar used these functions for giving an example of an orthonormal system as the space of square-integrable functions on the unit interval.

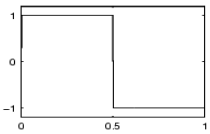

Fig.1 (a): Haar Wavelet Function.

Haar wavelet is simplest possible wavelet. Being non continuous it suffered with the technical disadvantage and hence it cannot be differentiated. Though this unique property of the can be beneficial for the analysis of signals with sudden transitions.

The mother wavelet function Ψ (t) of haar wavelet is ,

$$\Psi(t) = \begin{cases} 1, 0 \le t \le 1/2, \\ -1, 1/2 \le t < 1, \\ 0, otherwise. \end{cases}$$

Its scaling function $\emptyset(t)$ can be described as

$$\emptyset(t) = \begin{cases} 1, 0 \le t < 1, \\ 0, otherwise. \end{cases}$$

2.2'Daubechies' Wavelet

Ingrid Daubechies proposed this orthonormal wavelet family to define a discrete wavelet transform featured by maximal number of vanishing moments for given support.

Each wavelet of this family owns a scaling function called as father wavelet for generating the orthogonal multi resolution analysis.

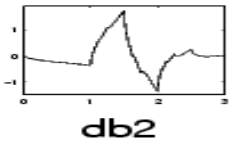

Fig.2: Daubechies Wavelet Function.

2.3'Biorthogonal' Wavelet

The linear phase property is needed for reconstruction of signal and image and the Biorthogonal wavelet family possesses this property. Two wavelets are used one for decomposition and other for reconstruction.

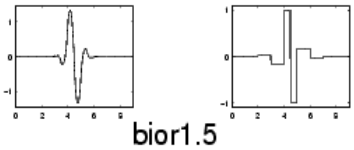

Fig.1 (b): Biorthogonal Wavelet Function.

2.4 'Coiflet' Wavelet

Ingrid Daubechies had proposed the coiflet wavelet for having better symmetry over the Daubechies wavelets to have scaling functions with vanishing moments. The coiflet wavelets have n coefficients and n can be 1,213,4,5,6 or 7. The nth coiflet has size of 6n. Whereas coiflet scaling functions have 2n-1 vanishing moments with their 2n vanishing moments of wavelet functions.

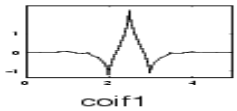

Fig.1 (c): Coiflet Wavelet Function.

2.5 'Symlet' Wavelet

The construction of symlet wavelet is very similar to the Daubechies wavelets. The Daubechies wavelets have maximal phase, the Symlet have minimal phase. In Wavelet Coefficients (Symlet, n), n can be any positive even number. The Symlet wavelet of size n has (1/2) n vanishing moments.

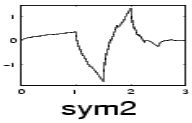

Fig.1 (d): Symlet Wavelet Function.

3. Principle Component Analysis (PCA)

After the feature extraction the PCA is applied on the training set images. The Principal Component Analysis (PCA) is one of the most successful methods that have been used in digital image processing and pattern recognition systems. The key purpose of PCA is to reduce the large dimensionality of the data space for describing the data efficiently.

Mathematically PCA can be defined as the orthogonal linear transformation which transforms the data to new coordinate system so that the greatest variance by any projection of the data which will come to lie on the first coordinate which gives the first principle component, the next second greatest variance on the second coordinate and so on.

On the other hand theoretically PCA can be described as the optimum transform for given least square terms. The dimensions of the data can be reduced by using PCA by retaining the characteristics of the dataset which contributes most to the variance by keeping lower order principle components and omitting higher ones. These considered lower order components often contains the most valuable aspects of the data. The PCA transformation is given by:

$$Y^{T=X^T} * W = V\Sigma$$

Here the matrix Σ represents the m-by-n diagonal matrix with non-negative real numbers on the diagonal and W Σ V^T is the singular value decomposition (svd) of X. PCA is sensitive to the relative scaling of the original variables. The Principle component analysis (PCA) is used here for the dimension reduction by performing a covariance analysis between factors [8]. PCA will give eigen values and eigenvectors which in turn will be used for the formation of the eigen faces which helps in reducing the size of the database for recognition of a test images. These images are deposited as their feature vectors in the database which are projecting each and every trained image to the set of Eigen faces obtained.

Thus here, by using PCA we can represent each image as a single n-dimensional vector, where n is the number of pixels in each image. Let $\{x1, x2, x_{N...}\}$ be a set of N training images. Principal component analysis (PCA) is a mathematical process that transforms a number of potentially correlated variables into a smaller number of uncorrelated variables called principal components. The main objective of using PCA is to reduce the

dimensionality of the dataset but retaining most of the original variability in the data as it is.

The Minimum distance Classifier is the next used here for the classification in order to identify the image in the training set to which the test image belongs. Classification is performed by comparing the feature vectors i.e. weight matrices of the images in the training set with the feature vector, the weight matrix of the test image which is to be recognized using minimum distance.

4. Proposed System

The training set images of face, ear and fingerprints are preprocessed and the features are extracted from these input images by using different wavelets in the second module of the proposed system as stated in above section II of this paper. Thus the second module produces the training set images in the form of single vectors containing the features extracted from facial images, ear images and from fingerprints. These feature vectors are then handed over to the next module of the system i.e. to PCA which will operate the feature vectors for getting the principle components for reducing the dimensions of the data to be stored. These principle components compute the eigen images which will be used further for recognition by using the decision making module.

Here the fusion of the principle components of face, ear and finger is done at the decision level. This is most important step of the algorithm where depending upon the above all steps one fair decision is made about the identification of the person for displaying the final result. The block diagram of the proposed system is shown here in Fig.1 Here if the test image is present in the database then that person's identification details will be get displayed as the final result of the system.

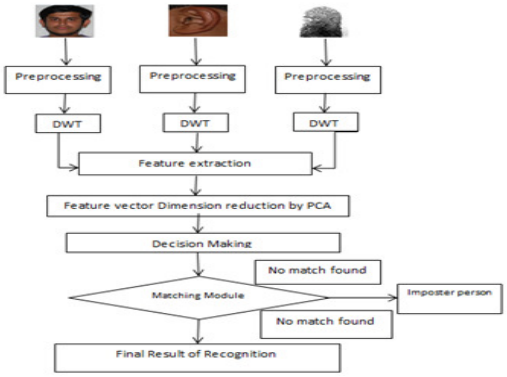

Fig.2: Block Diagram of Proposed System.

5. Experimental Results and Analysis

The proposed method is tested on the self-created database that contains a set of face images taken in different illumination of light and with different moods (facial expressions). The ear images of same persons are taken and stored along with the facial images which will form the training set. There are 9 different facial images of each person and 2 ear images (right ear and left ear) of same persons stored in the database. All the images are taken against a plane white background with different illumination of light with different facial expressions. The size of all training set images is made uniform throughout the system.

The MATLAB 2007b software is used for the implementation of the proposed multimodal biometric system. One of the person's images from self-created database is shown in Fig. 2 (a), (b) and (c),

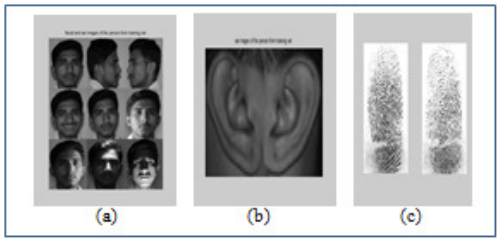

Fig.3: Database images of: (a) Facial, (b) Ear, (c) Finger.

The mean image is obtained for the computation of the principle components. The eigen values are obtained and plot of same is shown in Figure 3.

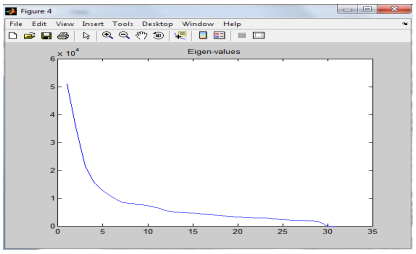

Fig.4: Eigen Values Obtained.

The eigen images are obtained by using the eigen vectors and eigen values the eigen images are shown in Figure 4.

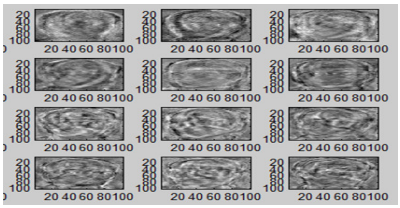

Fig.5: Eigen Images

The minimum distance classifier is used for recognizing the image to be of which class .The following Figure5 shows the distance between the weight vectors.

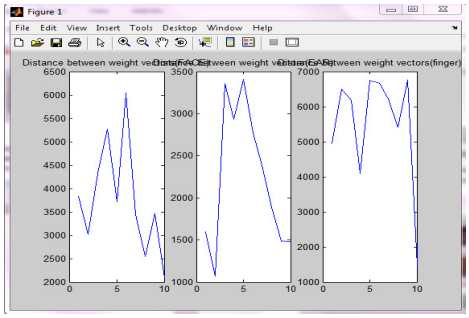

Fig.6: Minimum Distance of Weight Vectors.

The proposed system will identify the person by using the ear trait of the person. This is shown in following Figure 6,

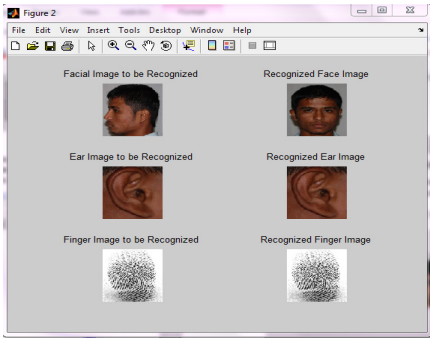

Fig.7: Final Result of Recognition.

The system is analyzed for self-generated training set and following table shows the analysis results,

Table 1: Results of Comparison of Recognition Using Wavelets

Wavelet used → / Trait Used ↓	%Accuracy With				
	Haar Wavelet	Daubechies wavelet	Biorthogonal wavelet	Coiflet Wavelet	Symlet Wavelet
Face	80	73	73	73	73
Ear	90	92	90	90	90
Thumb	98	97	98	98	97
Face and thumb	98	98	96	98	96
Face and Ear	82.38	82	82	80	82.36
Face, Ear and Thumb	100	100	100	100	100

This table shows that the recognition rate of the traits increases with the increase in number of traits used for recognition. Though the unimodal system using single biometric trait gives the better accuracy of recognition but is suffered from the limitations as stated in Section I of this paper. Hence the proposed multimodal biometric system using face, ear and finger offers a better recognition with authenticity and confidentiality.

4. Conclusion

In this paper we have explained multimodal biometric recognition system using face ear and finger as biometric traits. If we observe the results achieved, the percentage of recognition accuracy is increasing as we increase the number of biometric traits by providing a more authentic system. As results achieved with our experimentation are on self-generated database, hence we have not compared our results with existing results of other researchers. The purpose of our work is to develop a multimodal biometric system with additional traits for giving the more accurate, more authentic system by increasing and retaining the secrecy of the data.

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