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Face Recognition Using Wavelet Neural Network

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Abstract: Automatic face recognition system is an important component of intelligent human computer interaction systems for biometric. It is an attractive biometric approach, to distinguish one person from another. To perform Automatic face recognition system, the hybrid approach Wavelets face detection and Neural Network based Face Recognition is used. The face recognition accuracy is can be increased using a combination of Wavelet, PCA-FLD and Neural Networks. Preprocessing, feature extraction and classification rules are three crucial issues for face recognition. For preprocessing and feature extraction steps, we apply a combination of wavelet transform and PCA-FLD. During the classification stage, the Neural Network is explored to achieve a robust decision in presence of wide facial variations.

Keywords: Face Recognition, Wavelet, Eigenface, DWT, PCA, FLD, Neural Network.

I. INTRODUCTION

Face recognition is one of the most important applications of biometrics based authentication system in the last few decades. Face recognition is kind of recognition task pattern, where a face is categorized as either known or unknown after comparing it with the images of a known person stored in the database. Face recognition is a challenge, given the certain variability in information because of random variation across different people, including systematic variations from various factors such as lightening conditions and pose [1]. Computational methods of face recognition need to address numerous challenges. These types of difficulties appear because faces need to be represented in such a way that best utilizes the available face information to define a specific face from all the other faces in the database. Face pose is a specifically difficult problem in this aspect simply because all faces seem similar; specifically, all faces consist of two eyes, mouth, nose, and other features that are in the same location [9].

The research on machine face recognition has developed independently from studies on human face recognition. During the 1970s typical pattern classification methods, which use measurements between facial features or face profiles are used. During 1980s, works on face recognition is almost stable. Since the early 1990s the research focus on machine face recognition has grown significantly. The significant growth is because of the availability of real-time hardware, the growing need for surveillance applications, an increasing emphasis on commercial civilian research projects, and the studies on natural network classifiers, which stress real-time computation and adaptation. Face recognition system falls under two classifications: verification and identification. Face verification (one-to-one matching) that compares the face image against a template face images whose identity is being claimed. Face identification (one-to-many matching) that compares a query face image against all image templates in a face database.

Regardless of the method used, the most important concern in face recognition is dimensionality. Suitable methods are needed to reduce the dimension of the studied space. Working on higher dimension cases over fitting, where the system starts to memorize. Computational complexity is also an important problem when working on large databases. [2]

II. PROPOSED METHOD

Our proposed system consists of two techniques, they are

- Face recognition using Discrete wavelets
  1) Daubechies
  2) Symlets
  3) Coiflets

- Face recognition using Eigenface

These methods use PCA-FLD based recognition consists of two stages, namely training step in which the feature extraction, dimension reduction and adjusting the weight of neural networks have been performed and the recognition step to identify the unknown face image. The training stage includes the decomposing, feature extraction of reference images and the adjustment of neural network parameters. The extracting feature identifies the representational basis for images in the domain of interest. Subsequently, the recognition stage translates the input unknown image according to the representational basis, identified in the training stage. [3][4]

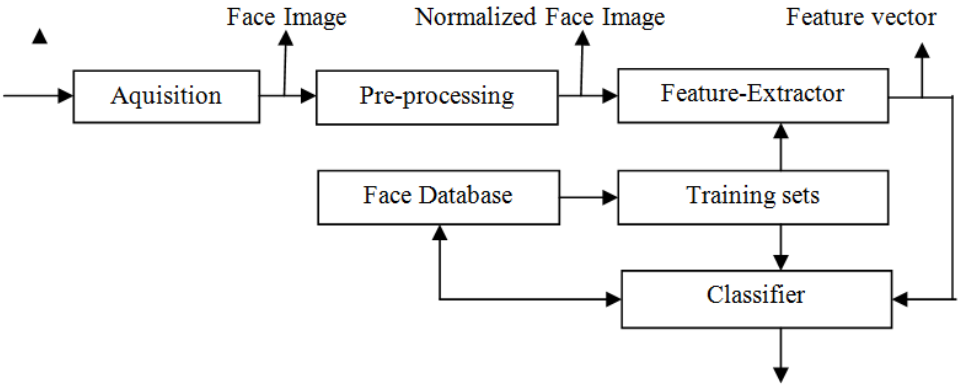

Fig.1 Face Recognition Steps

A. Algorithm

- There are three significant steps in the training stage. In the first step, wavelet transform (WT) is applied to decompose reference images.
- In the next step, Principal Component Analysis (PCA) is performed on the sub-images to obtain a set of representational basis by the selection of d′eigenvectors corresponding with the largest Eigen values and sub-space projection.
- The discriminability of PCA is further improved by adding FLD. But, to get a precise result, a large number of samples for each class is required.
- Finally, the feature vectors of reference images obtained by previous steps are used so as to train neural networks using feed forward algorithm.
- Processing in the recognition stage is similar to the training stage, except that recognition stage also incorporates steps to match the input unknown images with those reference images in the database by neural network.[4]

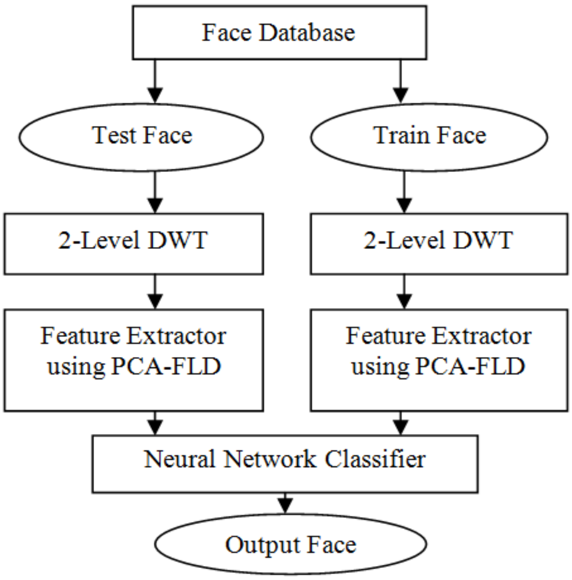

Fig. 2 Flowchart of the Proposed Algorithm

III. DECOMPOSING USING DISCRETE WAVELET TRANSFORM

A. Algorithm

Step 1: 2-D DWT is generally carried out using a separable approach, by first calculating the 1-D DWT on the rows, and then the 1-D DWT on the columns : DWTn[DWTm[x[m,n]].

Step 2: Two-dimensional WT decomposes an image into 4 “subbands” that are localized in frequency and orientation, by LL, HL, LH, and HH.Each of these sub bands can be thought of as a smaller version of the image representing different image properties.

Step 3: The band LL is a coarser approximation to the original image. The bands LH and HL record the changes of the image along horizontal and vertical directions, respectively. The HH band shows the high frequency component of the image

Step 4: Further decomposition to the LL sub band (two-level decomposition), leads to lower dimensionalities and a multi resolution image. We could perform higher levels of decomposition

Step 5: Since the LL part contains most important information and discards the effect of noises and irrelevant parts.

Step 6: We extract features from the LL part of the second-level decomposition. The reasons are the LL part keeps the necessary information and the dimensionality of the image is reduced sufficiently for computation at the next stage.[6]

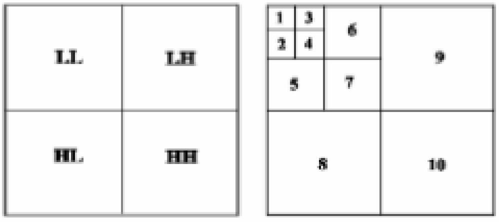

Fig. 2 Wavelet decomposition

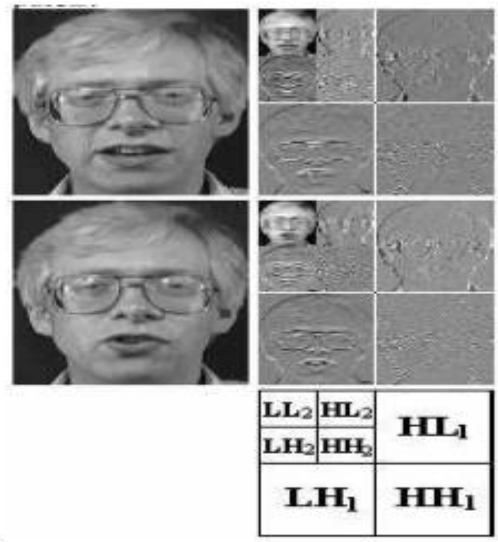

Fig. 3 Two-level wavelet decompositions of two images

B. Daubechies

Ingrid Daubechies, one of the brightest stars in the world of wavelet research, invented what are called compactly supported orthonormal wavelets -- thus making discrete wavelet analysis practicable.

The names of the Daubechies family wavelets are written dbN, where N is the order, and db the "surname" of the wavelet. The db1 wavelet, as mentioned above, is the same as Haar wavelet. Here is the wavelet functions psi of the next members of the family:

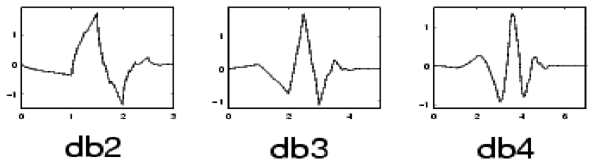

Fig. 5 Daubechies wavelets

C. Coiflets

Built by I. Daubechies at the request of R. Coifman. The wavelet function has 2N moments equal to 0 and the scaling function has 2N-1 moments equal to 0. The two functions have a support of length 6N-1.

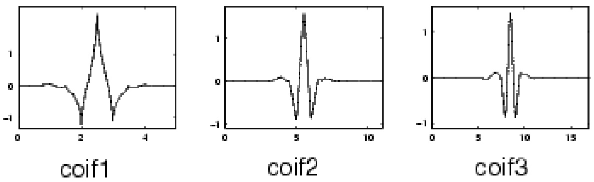

Fig. 6 Coiflets wavelets

D. Symlets

The symlets are nearly symmetrical wavelets proposed by Daubechies as modifications to the db family. The properties of the two wavelet families are similar. Here is the wavelet functions psi.

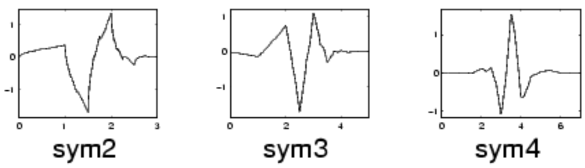

Fig. 7 symlets wavelets

IV. FEATURES EXTRACTION USING PCA AND FLD

A. PCA

Principal component analysis- PCA is a statistical approach. The main purpose of this approach is to reduce the dimensionality of the face image space to the similar intrinsic dimensionality of the feature space. This algorithm has various steps-[6][8]

Let total M images with dimension N×N i.e. N^2.

X_i is the mean of ith image.

i. Total mean

$$X = \frac{1}{M}\sum_{i=1}^{M} X\,i$$

ii. Subtract the total mean from individual mean of each image

$\Phi i = X_i - X$

iii. Form the normalized vectors

$A= [\Phi_1,\Phi_2,\dots\dots\dots\Phi_M] \quad N^2\times M$

iv. Co-variance matrix

$C = AA^T$

$$C = \frac{1}{M}\sum_{n=1}^{M}\phi_n\phi_n^T$$

Dimensions N^2 x M, M x N^2 = N^2 x N^2 dimensions So reverse it

$C = A^T A$

Dimensions M x N^2, N^2 x M = M x M

v. Compute eigen values and eigen vectors of covariance matrix, Select eigen faces with maximum eigen values

$$\lambda_1 > \lambda_2 > \dots\dots\lambda_n$$

$$V_1, V_2, \dots\dots\dots V$$

B. FLD

FLD is used to identify faces, by training and testing with several faces under different lighting. Fisher Linear Discriminant (FLD) analysis, also called Linear Discriminant Analysis (LDA). It is a statistical approach used for classifying samples of some unknown classes on the basis of training samples with known classes. The algorithm is as follows. [6][7]

i. Take images and classify them in C classes.

ii. μ_i is the mean vector of class i= 1, 2, 3……C

iii. Let M_i is the number of samples within class i

iv. Total number of samples M

$$M = \sum_{i=0}^{C} M$$

v. Calculation of within and between class scatter Within Class Scatter matrix

$$S_w = \sum_{i=1}^{C}\sum_{j=1}^{M_i}(y_j - \mu_i)(y_j - \mu_i)^T$$

y_j is the total mean of each sample $_{\text{Between}}$ Class Scatter Matrix

$$S_b = \sum_{i=1}^{C}(\mu_i - \mu)(\mu_i - \mu)^T$$

Mean of entire dataset

$$\bar{\mu} = \frac{1}{C}\sum_{i=1}^{C}\mu_i$$

Ratio of scatter between class and within class Maximize

$$\left(\frac{S_b}{S_w}\right)$$

V. EIGEN FACES

The basic concept behind the Eigen face method is information reduction. The scheme is based on an information theory approach that decomposes face images into a small set of characteristic feature images called ‘Eigenfaces’, which are actually the principal components of the initial training set of face images. Recognition is performed by projecting a new image into the subspace spanned by the Eigenfaces (‘face space’) and then classifying the face by comparing its position in the face space with the positions of the known individuals.

A. Algorithm

1) Creating the Eigenfaces: Prepare a training set of face images. The pictures constituting the training set should have been taken under the same lighting conditions, and must be normalized to have the eyes and mouths aligned across all images. They must also be all resampled to the same pixel resolution. Each picture has R rows and C columns.[2]

Step 1: Convert each picture in the training set into a vector of length R x C by concatenating the rows of pixels of the original image.

Step 2: If there are n training set images then create a matrix, M where the number of rows = N and the length of each row = RxC. Each row will be represented by one of the image vectors.

Step 3: Calculate the mean image A of the N image vectors. Subtract A from each row of M to obtain the matrix T.

Step 4: The covariance matrix, S is given by S=T‘.T where T‘represents the transposed matrix of T.

Step 5: Calculate the eigenvectors and eigenvalues of S. R x C no of eigenvectors has been obtained but the main idea about the principal components is to store only the eigenvectors with the highest value.

These Eigenfaces can now be used to represent both existing and new faces: A new (mean-subtracted) image has been projected on the Eigenfaces and thereby record how that new face differs from the mean face. The eigenvalues associated with each Eigenface represent how much the images in the training set vary from the mean image in that direction. Information has been loosed by projecting the image on a subset of the eigenvectors, but the lose has been minimized by keeping those Eigenfaces with the largest eigenvalues. [2]

2) Recognising a face:

Step 1: Obtain a test image, I

Step 2: Subtract the mean image A from the test image.

D=I-A

Step 3: Find its projection on the face space.

P = Eigenfaces‘ x D

VI. FEED FORWARD NEURAL NETWORKS

A large neural network for all people in the database was implemented. After calculating the Eigenfaces, the feature projection vectors are calculated for the faces in the database. These feature projection vectors are used as inputs to train the neural network. [10]

When a new image is considered for recognition, its feature projection vector is calculated from the Eigenfaces, and this image gets its new descriptors. These descriptors are fed to the neural network and the network is simulated with these descriptors, where the network outputs are compared. By looking at the maximum output the new face is decided to belong to the class of person with this maximum output.

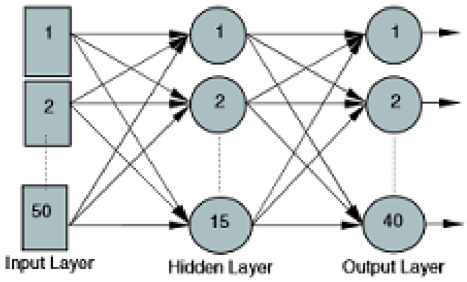

Fig. 8 Architecture of proposed Neural Network

VII. EXPERIMENTAL RESULTS

The face image database used in our experiments consists of 90 subjects with 5 face images available for each subject with different expressions. The test image database consists of 36 images with two face images for each subject with different expressions. Some samples of images from this database is shown in Fig. 2. These face images includes only the frontal faces with different expressions and all the images are in PGM format. In the experiments, all face images in the database were resized to 128 x 128. One of the images as shown in Fig. 11 is taken as the Input image(query sample) from test image set. The mean image and reconstructed output image by dwt method, is as shown in Fig.12.

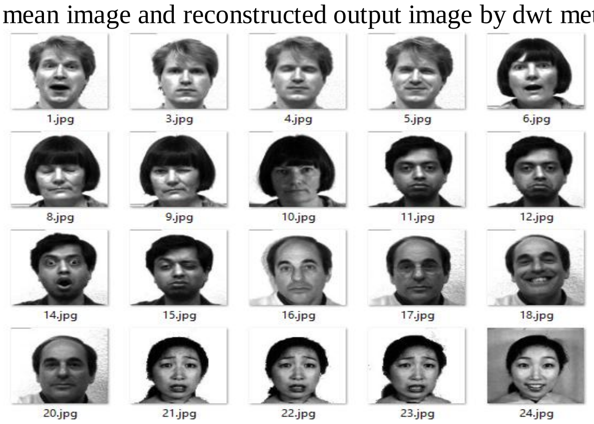

Fig. 9 Sample Database

The entire test image compares with the image of our training data set using wavelet neural network and Eigen face based methods. For wavelet neural network we get result 30 times means 30 images are recognized correctly by the face images of correct person

For Eigen face method we get result 22 times means 22 images are recognized correctly by the face images of correct person. On the basis of the recognition rate we have compared the two techniques. . In noisy images the DWT will be of higher efficiency and it converge faster than the Eigenface. It can also be seen that during image reconstruction the higher the number of Eigenfaces chosen the better and the closer the reconstructed image to the original but at the expense of computational difficulty, hence a proper choice for the number of Eigenfaces to be chosen so as to reduce computation complexity. Considering above, DWT methods have better recognition rate than a Eigen face based method. The recognition plot which has epoch versus training error is shown in fig below, by observing the plot we can say that as the number of epoch increases as the training error decreases. Basically The training error is used to update the weights. During iterative training of a neural network, an Epoch is a single pass through the entire training set, followed by testing of the verification set.

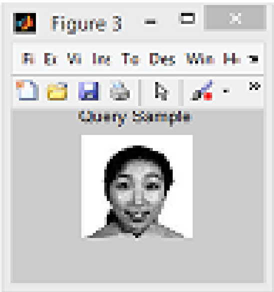

Fig. 10 Query sample

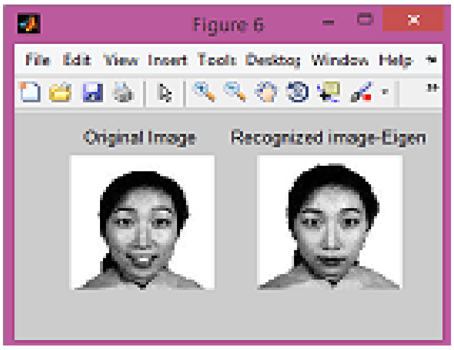

Fig. 11 Recognized Image

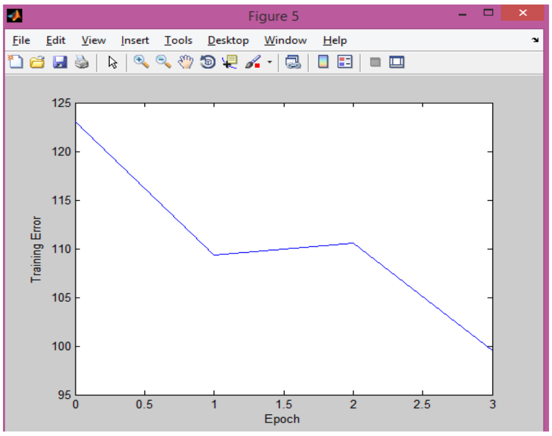

Fig.12 Recognition plot

Table 1 Recognition Rate

Method	**Recognition Rate**
Daubechies	92%
Symlets	90%
Coiflets	91%
Eigen faces	78%

VIII. CONCLUSION

The experiments that we have conducted on the database vindicated that the combination of Wavelet, PCA-FLD and FFNN exhibits the most favorable performance, on account of the fact that it has the lowest overall training time, the lowest redundant data, and the highest recognition rates when compared to Eigenface Approach method. The performance of the two algorithms were compared and the performance of DWT methods is higher than that of Eigenface since it converge with relatively the same recognition rate but the former converge faster than the latter. Our proposed method in comparison with the present hybrid methods enjoys from a low computation load in both training and recognizing stages. As another illustration of the privileges of our method, we can mention its great precision

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