PERFORMANCE ENHANCEMENT OF FACE RECOGNITION SYSTEM USING PRINCIPAL COMPONENT ANALYSIS MERGED WITH DISCRETE WAVELET TRANSFORMS

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ABSTRACT

Performance of face recognition system can be enhanced by proposed technique titled as PCA merged with Discrete Wavelet Transform (DWT) instead of using the conventional PCA technique. In this technique to reduce the computational complexity of traditional PCA the size of the image is first reduced by taking the DWT of it. After applying the DWT the facial features of the image are extracted by calculating the Eigenface of the image with size already reduced by taking DWT. As a result of this process the size of database will reduce to one-fourth of the conventional PCA in which the facial features are extracted directly from the image by calculating the Eigenface. The size of the train database is reduced with the proposed technique which reduces the processing time of the face recognition without losing the accuracy. Performance of face recognition system is enhanced in terms of low processing time as shown by comparing the experimental results of conventional PCA and the proposed technique in this paper.

Keywords: *Principal Component Analysis (PCA), Discrete Wavelet Transform (DWT), Eigenface, Covariance metric*

INTRODUCTION

Face recognition has gained great attention in field of biometric research because of its robustness compared to finger printing which may be not possible with users finger being injured, passwords and pins may be forgotten or guessed by unauthorized person and cards or tokens may be lost.

Research in face recognition system has started in early 60s. In 1966 first attempt was made to automate the face recognition by a semi-automated man-machine system[1]. From early to mid-1970s the technique used was pattern classification, research on face recognition was dominant in 1980s and interest in this field grew significantly in early 1990s. The techniques proposed some earlier researchers are the holistic approaches that have proved effective on large databases experiments[2].

Basically two types of approaches are used for face recognition systems named as constituent based approach (feature based technique) and faced based approach (holistic). In the constituent based approach relation between the facial features i.e. eyes, nose, mouth and face boundary[3] is used for recognition. The success achieved by this approach is dependent on the feature extraction scheme[4]. The other method i.e. the face based approach is based on the PCA or information theory. In this approach the most significant information is extracted from the entire face represented in terms of coordinate system economically known as eigenface[5,6]. But large computational load or processing time is one of the main limitations in conventional PCA[4].

Other techniques used for face recognition are the Independent Component Analysis (ICA) where faces are supposed to be linear mixture of some unknown dormant variables[7] and Hidden Markov Models (HMMs)[8]. Almost all the techniques were focused on recognition rate without considering the compression rate. However, compression of database is an important factor for several applications including less space consumption of hard drive and reduction of computational time. In this work, both the recognition rate as well as compression rate is taken into account in order to provide broader perspective of the face recognition system.

PCA

PCA has been proven to be one of the most successful techniques widely used for image processing[9]. The purpose of PCA is to reduce the large dimensionality of the image by converting image matrix to a vector and the images are then represented by their eigenfaces[10]. It converts the image into a matrix and then to a vector array. For more than one image the vectors are placed in a series of columns. Mean matrix, center matrix and covariance matrix are calculated. The eigenvectors and

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eigen-values of covariance matrix are also calculated. The eigenvectors with zero eigenvalues are less important and can be removed for compression. The PCA has numerous applications in image processing[11] including dimensionality reduction of an image[10]. To achieve dimensionally reduced images, the images are first transformed into a matrix as follows.

$$X = [A(i)] \tag{1}$$

Where $A(i)$ is an image vector of order $P \times 1$ for $1,2,3 \ldots\ldots m$. To apply PCA it is necessary to define some important terms such as mean matrix, center matrix and covariance matrix. The mean matrix is calculated as:

$$M = \frac{1}{M}\sum_{i=1}^{m} A_i \tag{2}$$

The center matrix is the difference between image vector and mean matrix. It is given as follows:

$$Y = [(A_{(1)} - M)(A_{(2)} - M) \ldots \ldots (A_{(m)} - M)] \tag{3}$$

The covariance matrix is the multiplication of center matrix and its transpose.

$$C = \sum_{i=1}^{m} YY' \tag{4}$$

Using formulas, the eigenvectors and eigen-values can be calculated for a covariance matrix as:

$$|\lambda I - C| = 0 \tag{5}$$

$$CX = \lambda X \tag{6}$$

Where C is the covariance matrix, X is eigenvector, λ is the corresponding eigenvalue and I is the identity matrix.

These eigenvectors are then sorted in descending order according to their eigen-values, because eigenvectors with the largest eigen-values have the greatest variance in the image while the eigenvectors with smallest eigen-values have least variance[10,12]. For compression purpose those eigenvectors can be removed that have zero eigen-values or they do not contribute more than a threshold value. The process of PCA is summarized in Figure 1.

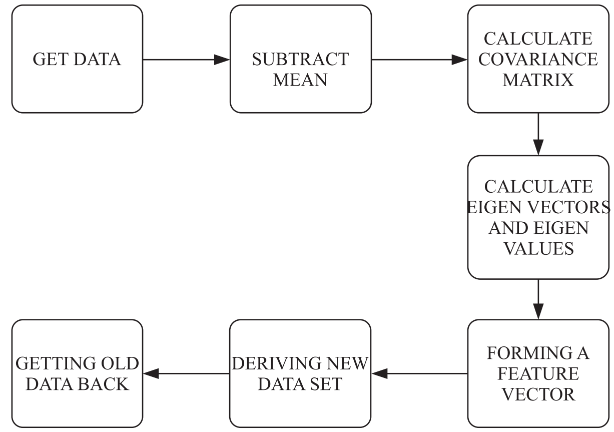

Figure 1: Block diagram of PCA

DWT

DWT is a popular tool used in image processing for compression[13]. It employs low and high pass filters subsequently. These filters are first applied to the rows of an image, producing two new images containing coarse row coefficients and detail row coefficients. The filters are then applied to the columns of each new image, which produces four new images.

These new images are then named as sub-bands[14]. These sub-bands present information of an image in frequency domain. By applying inverse DWT the transformed image can be converted to original one. These sub-bands are LL, HL, LH and HH. LL sub-band retains the detail information of the image and thus it is considered as a reduced version of the original image[14]. HL contains horizontal, LH contains vertical and HH gives diagonal information of the image In DWT, only LL sub-band is processed for decomposition[14] as this sub-band contains most of the image information. Each level of decomposition creates four new images from original $N \times N$ pixel of image. The size of this new image is reduced to one-fourth of the original size.

METHODOLOGY

The methodology consists of two main steps:

- Training the Database
- Recognition of the Faces in the Training set

Each step mentioned above have sub-steps given below:

Training of database (Figure 2)

- Read face images from the Database folder
- Then take the DWT of these images
- Normalize all the face images
- Hence calculate the Eigenvectors of Covariance Matrix
- Find significant Eigenvectors of Reduced Covariance Matrix
- Calculate Recognizing Pattern Vectors (RPV) or weight vectors for each image

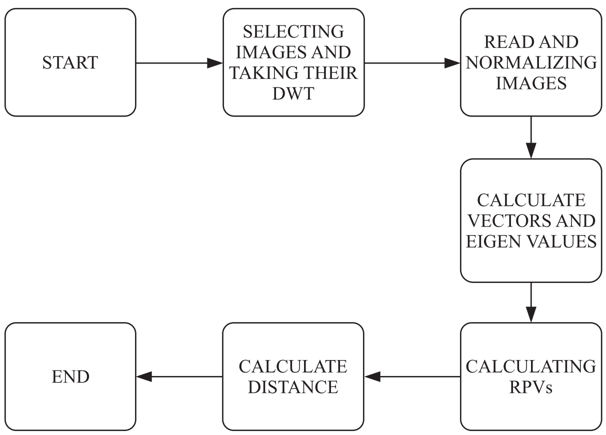

Figure 2: Training the Database

Recognition of the Faces in the Training (Figure 3)

- Select an image which is to be tested
- Take DWT of the image
- Normalize all the face images
- Calculate the RPV of image using Eigenvector of Covariance Matrix
- Find the distance of this input image RPV from average RPVs of all the images in the training
- Find the image from which the distance is minimum
- Image in the training set having minimum distance from the test image is considered as matched with test image
- There should be a threshold for the minimum distance which will decide that a test image with distance closed than the threshold will be considered matched with a training image.

Implementation of DWT

By implementation of the DWT in the training the goal of data compression begins before going in to the next step dimensionality reduction of the images by PCA. As a result of applying the DWT we get four sub-bands of the image as shown in the Figure 4 & 5.

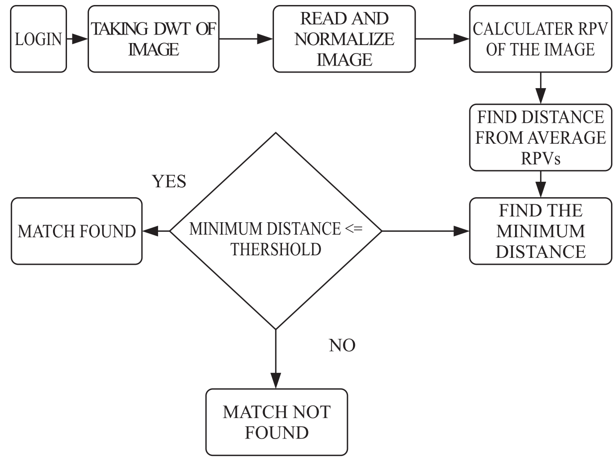

Figure 3: Recognition of the Faces in the Training set

Figure 4: Image before DWT

Figure 5: DWT Sub-bands

These sub-bands show the information of in image in frequency domain. The most prominent details of the image are contained in the first sub-band which is known as the LL band.

Figure 6: Image after implementing DWT. After applying DWT, image is reduced to 64x64 pixels from 128x128 pixels.

Figure 7: Mean Face

Figure 8: Original images of ORL Database (128x128)

Figure 9: Some examples of ORL database eigenfaces (330x1)

We use the LL band and discard the rest of the bands and then perform PCA on this LL band and that is how the image is compressed before going in to PCA. The compression rate of DWT is shown in Figure 6.

Implementation of PCA

Now PCA is implemented on an image of size 64x64 pixels. The Database contains 40 images, these images are arranged in vector array in such a way that each vector represents an image. The mean matrix is calculated using these column vectors as shown in Figure 7.

Some of the original images of ORL database are given below in Figure 8.

After the compression through PCA, some of the images are shown in Figure 9. Detection of true positive face in face recognition system is based on the eigenvector comparison. The test image is first passed through all the steps in processes mentioned earlier to get the eigenvector which is then compared with the eigenvectors in the training set. The Euclidean distance is found between the RPV of the test image and the training images to take decision as given below:

$$E_d = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \quad (7)$$

Euclidean distance calculated in above equation is inversely proportional to the correlation between the training images and the test image[13]. A threshold value is selected in order to prevent the false acceptance detection of an image. If the Euclidean distance is greater than the threshold the image is not true detected and is rejected by the face recognition system.

RESULTS

Results for this project were obtained using two standard databases.

- AT&T database (formerly known as the ORL database of faces)
- MUCT database

AT&T database

The frontal position images of all the 40 subjects were copied to the training folder. These images were trained. The threshold value was set to (0.68). First all the images of 40 subjects were compared with training set to find the number of true acceptance (TA) and true rejection (TR). The readings were taken for both the techniques PCA and principal component analysis merged with discrete wavelet transform (PCA+DWT). Then each subject was removed from the training folder one by one and the images were trained. In this test the untrained images of each subject was compared with the training set to find the number of false acceptance (FA) and false rejection (FR). The details of this test and comparison of the two techniques is given in the Figure 10.

From the graph in Figure 10 it is clear that the accuracy of PCA+DWT is 74.5% and PCA is 73.125% for AT&T database.

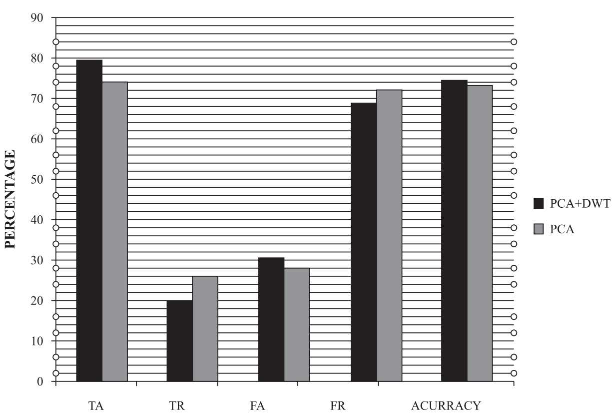

Figure 10: Accuracy comparison of PCA with PCA+DWT

MUCT database

Images of different test objects are distributed in MUCT database according to the Table 1.

Step 1: In this test the front pose images of subjects 000-090 were selected. These 91 subjects were divided into two folders i.e 91a and 91b. 91a contained the first 46 subjects and 91b contained the remaining 45 subjects.

Table 1: Image distribution in MUCT database

Lightening Set	Subject ID	No. of Subjects	No. of Images
qrs	**000-090**	**91**	**1365**
tuv	200-307	108	1620
wx	400-451	52	520
yz	600-624	25	250
		Total = 276	Total = 3755

The test images were also divided in two folders i.e 91ta and 91tb. 91ta contained the images of first 46 subjects in four different poses i.e a,b,c,d. 91tb contained the images of the remaining 45 subjects in four different poses i.e a,b,c,d.

Step 2: The folder 91a was trained and folder 91ta was compared with training set to find TA and TR. The folder 91tb was compared with the training set to find FA and FR.

Step 3: The folder 91b was trained and folder 91tb was compared with training set to find TA and TR. Then the folder 91ta was compared with the training set to find FA and FR. Similar steps were taken to find the TA,TR,FA and FR for the remaining groups of subjects in the Table 1. These tests were taken for threshold values i.e (0.75). The experimental results for these tests are summarized with the help bar graph in Figure 11.

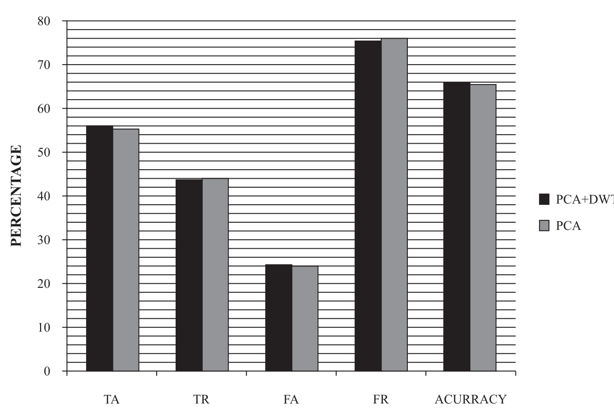

Figure 11: Accuracy comparison of PCA with PCA+DWT

PROCESSING TIME RESULTS

Processing time comparison between PCA and PCA+DWT is performed using the MUCT database.

The size of an image in MUST database is 480x640. After applying the DWT size of the image is reduced to 324x244. The Eigen faces calculated by PCA is of the size 307,200 x N for N number of faces and the Eigen faces calculated by PCA+DWT is of the size 79,056 x N for N number of faces which is one-fourth of 307,200 x N. This clearly shows that processing time for training same number of images with PCA+DWT will be less than the PCA without losing the accuracy. Figure 12 and Figure 14 shows the processing time comparisons of PCA with PCA+DWT.

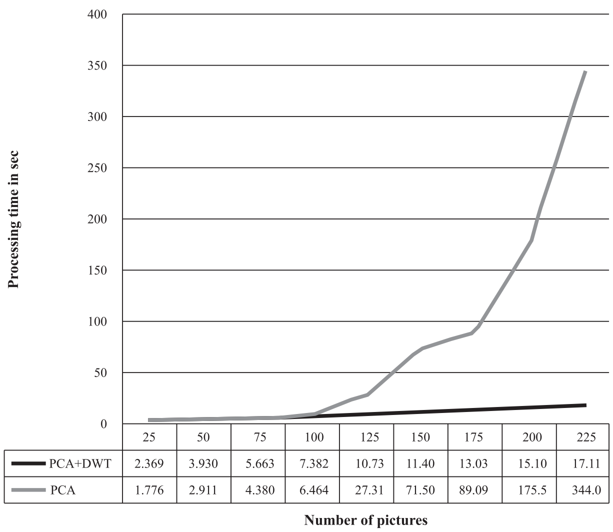

Figure 12: Processing time comparison for training of images (PCA) v/s (PCA+DWT)

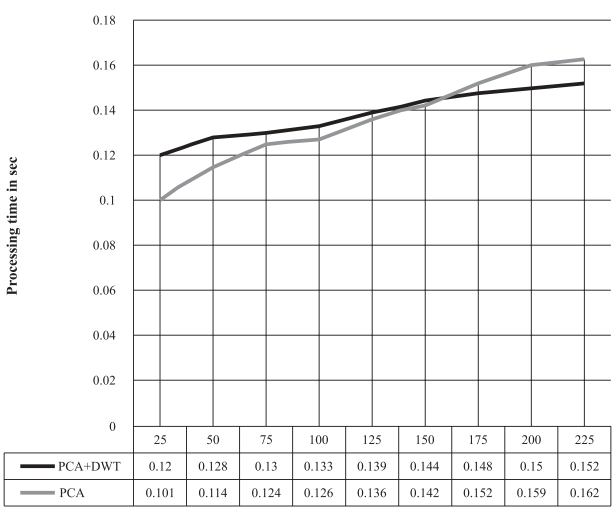

Figure 13: Processing time comparison for testing an image (PCA) v/s (PCA+DWT)

The processing time of training of images increases almost exponentially with the number of images in case of conventional PCA as shown in Figure 13 while it is linear and very low in case of proposed technique.

CONCLUSION

The paper propose a novel approach for face recognition by merging two different techniques, DWT and PCA i.e PCA merged with DWT. The implementation results of the proposed method shows almost the same recognition rate as conventional PCA but with an improved compression rate i.e the database is reduced to one-fourth in size. As a result of the high compression rate the proposed technnique reduces the processing time as compared to conventional PCA. This technique also reduces the required disk size of training set of the database which is a prominent improvement in case of very large databases that requires high disk space.

FUTURE WORK

The proposed method has focused on the compression rate reduction and processing time reduction of face recognition but still there are some other issues in face recognition such as light intensity and poses variations. In future, there is a need of research to overcoming these limitations of light intensity and poses variations. One can also try for further compression of database as well as improved recognition rate by using other techniques.

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