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A Hybrid DWT, PCA and ICA Features for Face Recognition using Neural Network and k-NN Classifiers

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Abstract – **Face recognition is one of the most relevant applications of image analysis. It is a relevant subject in pattern recognition, computer graphics, image processing neural networks and psychology. Face recognition depends on the particular choice of features used by the classifier for that purpose we are using three different technologies i.e. PCA, ICA and Neural Network in which Neural Network is working as a good classifier. The main work of classifier is to obtain the optimal subset of features under some criteria leading form a given set of extracted features and also can be displayed on future trials using novel (unseen) test data. The features of images found by PCA depend only on pair wise relationships amongst pixels in the image database. In this paper, the face recognition system based on DWT-PCA-ICA and Neural Network has been developed and its performance has been compared with k-NN classifier method. Neural Network is used to improve the accuracy of our recognition system by auto threshold setting. Simulation Results show that the proposed research work gives the best performance.**

Keywords **–ICA, PCA, Neural Network.**

I. Introduction

Face recognition is an important tool in order to overcome the problems of today's world. It is applicable to several real-world applications like surveillance, authentication human/computer interface and video surveillance. However research level in this field is still young. Face recognition heavily depends on the particular choice of features extracted by the classifier. Usually starts with to derive an optimal subset of features under some specific criteria from a given set of features and then attempts to leading to high classification performance with the expectation that give similar performance that can also be obtained on future trials using novel and unseen test data.

Main challenge of face recognition is to build an automated system which equates human ability to recognize faces. Although humans are quite so good in identifying known faces, we must deal with a large amount of unknown faces when we are not very skilled. The computers, with an almost limitless, intelligence memory and fast computational speed, should overcome human's limitations up to certain level. Face recognition remains as an unsolved problem and a demanded technology. In fact, the earliest works on this subject were made in the 1950's in psychology [1]. They came attached to other issues like interpretation of faces, emotions or perception of face gestures.

Engineers started to show interest in face recognition in the 1960's. One of the first researches on this subject was Woodrow W. Bledsoe. In 1960, Bledsoe, along other researches, started Panoramic Research in Palo Alto, California. During 1964 and 1965, Bledsoe, along with Charles Bisson and Helen Chan, worked to recognize human faces on using computers [2]. Because the funding of these researches was provided by an unnamed intelligence agency, little of the work was published. He continued his researches later at Stanford Research Institute [2]. Bledsoe designed and implemented a semi-automatic system. He described most of the problems that even 50 years later Face Recognition still suffers - variations in head rotation, illumination, facial expression and facial aging. Researches continues there research, trying to measure subjective face features such as ear size or distance between eye and ear. In 1973, Fischler and Elschanger tried to measure similar features automatically [3]. Their algorithm used local template matching and a global measure of fit to find and measure facial features.

There were other approaches back on the 1970's. Some researchers tried to define face as a set of geometric parameters and then perform some pattern recognition based techniques on those parameters obtain from face. But the first one that developed a fully automated face recognition system was Kenade in 1973 [4]. The algorithm extracted

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sixteen facial parameters automatically. He got a correct identification rate of 45-75%. He demonstrated that better results were obtained when irrelevant features were not used. In the 1980's there were a diversity of approaches actively followed by other researchers, most of them continuing with their previous tendencies. Some works tried to improve the methods used measuring subjective features. For instance, Mark Nixon presented a geometric measurement for eye spacing [5]. The template matching approach was improved with strategies such as "deformable templates". This decade also brought with new approaches for recognition. Some researchers build face recognition algorithms using artificial neural networks [6].

The first mention to Eigen faces in image processing, a technique that would become the prevalent approach in coming years, was made by L. Sirovich and M. Kirby in 1986 [7]. Their methods were based on the PCA i.e. Principal Component Analysis. Their goal was to makeup an image in a lower dimension without losing no such information, and then reconstructing it in new faces [8].

The 1990's saw the broad recognition of the mentioned Eigen face approach as the basis for the state of the art and the first industrial applications. In1992 Mathew Turk and Alex Pentland of the MIT presented a work which used Eigen faces for recognition [9]. Their algorithm was able to locate, track and classify a subject's head.

Principal Component Analysis (PCA) is a technique among the most common feature extraction techniques used in Face Recognition. After a preprocessing and normalization stage to the image, PCA (Principle Components Analysis) is applied to recognize a specified face. If the face not recognized correctly, then more features are extracted face color and moment invariant. Recent research work in the field of face recognition can be seen in [12], [13], [14], [15] and [16].

II. PCA MODULE

This is the module which contains the implementation of PCA. The extracted images stored in the fdata.dat file forms the dataset for the PCA. Depending upon the No. of images stored say 'n', a matrix ' A ' is formed of size 25600×n. The flow diagram of PCA is shown in Figure 1. The following steps are carried out:

i. *Center data:* Each of the training images is centered by subtracting the mean image from each of the training images. The mean image is again a column vector such that each entry is the mean of all corresponding pixels of the training images.

ii. *Covariance matrix:* Now the centered training images in the matrix 'A' is multiplied with its transpose to form a covariance matrix L.

$$L = A^T A \ldots\ldots\ldots\ldots \text{ n×n Matrix} \qquad (1)$$

iii. *Computing the Eigen Faces:* The 'n' Eigen faces are computed using the equation:

$$V = A * V * (\text{abs}(\text{D}))^{-0.5} \qquad (2)$$

iv. *Projecting of Training Images and Test Images:* Each of the centered training images (X_i) is projected onto the eigenspace. The dot product of the image with each of the ordered eigenvectors is calculated to project an image onto the Eigen space,

$$\tilde{x}^i = V^T \bar{x}^i \qquad (3)$$

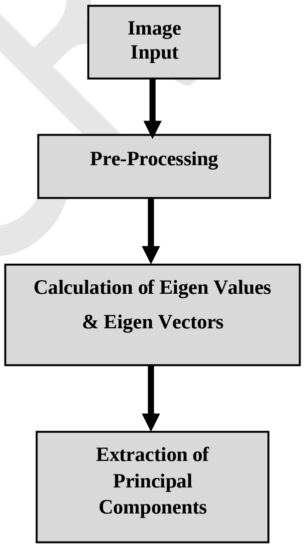

Figure 1: Flow diagram of PCA module

III. DISCRETE WAVELET TRANSFORM (DWT)

Discrete Wavelet transform (DWT) is a mathematical tool for hierarchically decomposing an image. It is useful for processing of non-stationary signals. The transform is based on small waves, called wavelets, of varying frequency and limited duration. Wavelet transform provides both frequency and spatial description of an image. Unlike conventional Fourier transform, temporal information is retained in this transformation process. Wavelets are created by translations and dilations of a fixed function called mother wavelet. This section analyses suitability of DWT for image watermarking and gives advantages of using DWT as against other transforms.

The DWT is nothing but a system of filters. There are two filters involved, one is the "wavelet

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filter", and the other is the "scaling filter". The wavelet filter is a high pass filter, while the scaling filter is a low pass filter. DWT includes many kinds of transforms, such as Haar wavelet, Daubechies wavelet, and others. Figure 2 shows the workflow of DWT.

An advantage of DWT over other transforms is it allows good localization both in time and spatial frequency domain. Because of their inherent multi-resolution nature, wavelet coding schemes are especially suitable for applications where scalability and tolerable degradation are important. Applying IDWT to LL, HL, LH, and HH, we can get four different frequency's images that are low frequency image, middle-low frequency image, middle high frequency image, high frequency image separately.

Characteristics of DWT

- Wavelet Transform is computationally efficient and can be implemented by using simple filter convolution.
- With multi-resolution analysis, image can be represented at more than one resolution level. Wavelets allow image to be described in terms of coarse overall shape and details ranging from broad to narrow.
- Magnitude of DWT coefficients is larger in the lowest bands (LL) at each level of decomposition and is smaller for other bands (HH, LH, and HL).
- The larger the magnitude of wavelet coefficient, the more significant it is.
- Watermark detection at lower resolutions is computationally effective because at every successive resolution level, less no. of frequency bands are involved.
- High resolution sub bands help to easily locate edge and textures patterns in an image.

IV. ICA MODULE

This is the module which contains the software implementation of ICA. The extracted images stored in the fdata.dat file forms the dataset for the ICA. Depending upon the No of images stored say 'n' a matrix 'A' is formed of size 25600×n. The steps are given in the following paragraphs:

Pre-processing and PCA

The output of PCA module is given as input to the ICA module as shown in the figure 4. Steps for preprocessing are as follows:

i. *Centering:* The most basic and necessary preprocessing is to center x, i.e. subtract its mean vector m = E{x} so as to make x a zero-mean variable. This implies that s is zero-mean as well.

ii. *Whitening:* We transform the observed vector x linearly so that we obtain a new vector x̃ which is white, i.e. its components are uncorrelated and their variances equal unity. In other words, the covariance matrix of x̃ equals the identity matrix:

$$E\{\tilde{x}\tilde{x}^T\} = I$$

iii. *Learning:* Learning is carried out through permuted x̃ which is of length M, in batch blocks of size B, adjusting weights, w, at the end of each block. The process is repeated every F counts till convergence. The updated weight matrix, w which was obtained by learning process is applied along with the whitening matrix, wz in the following equation:

$$uu = w * w_z * xx$$

iv. *Representations of Test Image:* The pre-processed test image is contained in the row of C_{test}. The centering of test image is carried out with respect to mean of training images.

$$D_{test} = C_{test}\text{-ones}(1,1)\text{*mean}(C)$$

v. *Cosine Distance:* It computes the cosine (normalized dot product) between training vectors and test vector. Output is a matrix of cosines.

$$C = \frac{B_{test}.B_{train}}{|B_{test}||B_{train}|}$$

vi. *Setting up of Threshold value and showing up of Result:* The threshold value is set by trial and error method then the face is recognized else the system gives a message that image is not matched. In the present scenario the threshold value is set to 0.74.

V. NEURAL NETWORKS

The general Neural Network approach contains following steps:

- Neural network creation
- Configuration
- Training
- Simulation

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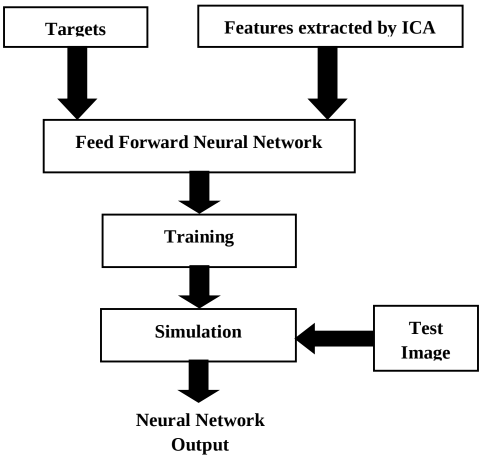

Figure 2: Flow diagram for Neural Network method

Figure 2 depicts the functionality of Neural Network in our project, which accept the features of training images and test image as an input a predefined target value has been set to perform feed forward neural network with gradient descent back propagation neural network algorithm in the presence of supervise learning, this algorithm is used to reduce the overhead and increase the accuracy of network and we use sigmoid transfer function to perform calculation at output layers. With the help of these all function desired output is generated.

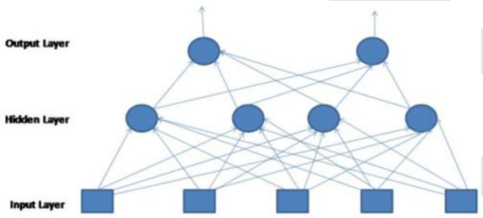

Figure 3: An example of a simple feed forward network [11]

Feed-forward ANNs (figure 3) as the name implies allow signals to travel in one way only; from input to output layer. There is no feedback loops or recurrent loops i.e. the output of any layer will not affect that output of the same layer. Feed-forward ANNs is also tend to be a straight forward networks that is associated with inputs outputs. They are highly used in pattern recognition and classification. The below diagram depicts the functionality of feed forward neural network.

The Network layers

The general type of neural network consists of three groups of layers, or three groups of units: first one is a layer of "input" units which is always is connected to a second layer i.e. layer of "hidden" units, which is finally connected to a layer of "output" units. Figure 3 shows the representation of all layers of neural network.

The Learning Process

There are basically two major categories of learning methods used for neural networks Supervise learning methods and unsupervised learning method in our project we work or perform simulation of neural network under supervised learning mechanism Supervised learning which work as an external teacher or guide, so that each output unit is told to perform what should be desired response to the respected input signals. Global information may be required during learning process. Error convergence is the main concern issue of supervise learning, i.e. the minimization of error between the desired and computed unit values of network. Here the main aim is to find a set of weights which minimizes or reduce the error up to precise level. The least mean square (LMS) convergence is well known method for many learning paradigm.

Transfer Function

The whole behavior of our Neural Network totally depends on both the weights and the input-output function i.e. transfers function that is specified in the all units. There are basically three categories of Transfer Functions:

- Linear (or ramp)
- Threshold
- Sigmoid

For linear units or for the linear transfer function, the output activity is directly proportional to the total weighted output units. For threshold units or for threshold transfer function, the output unit outputs are set at one of two levels, which totally depending on whether the total input of output unit is greater than or less than some predefined threshold value. For sigmoid units or for sigmoid transfer function, the output varies or changes continuously but not linearly as the inputs of input unit changes.

VI. K-Nearest Neighbours Classifier

In pattern recognition, the k-Nearest Neighbors algorithm (k-NN) is a non-parametric method used for classification and regression. In both cases, the input consists of the k closest training examples in the feature space. The output depends on whether k-NN is used for classification or regression:

- In k-NN classification, the output is a class membership. An object is classified by a majority vote of its neighbours, with the object being assigned to the class most common among its k nearest neighbours (k is a positive integer, typically small). If k =

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1, then the object is simply assigned to the class of that single nearest neighbour.

- In k-NN regression, the output is the property value for the object. This value is the average of the values of its k nearest neighbours.

k-Nearest neighbor is an example of instance-based learning, in which the training data set is stored, so that a classification for a new unclassified record may be found simply by comparing it to the most similar records in the training set.

Algorithm

Given a query point$x$, it is ensured that the instances in a database are not revealed to other databases in the nearest neighbor selection, and that the local classification of each database is not revealed to other databases during global classification.

In order to determine the points in their database that are among the k nearest neighbors of x, each node calculates k smallest distances between x and the points in their database (locally).

After each node determines the points in its database which are within the k^{th} nearest distance from$x$, each node computes a local classification vector of the query instance where the i^{th} element is the amount of vote the i^{th} class received from the points in this node's database which are among the k nearest neighbors of x.

A very common thing to do is weighted kNN where each point has a weight which is typically calculated using its distance. For e.g. under inverse distance weighting, each point has a weight equal to the inverse of its distance to the point to be classified. This means that neighboring points have a higher vote than the farther points.

It is quite obvious that the accuracy might increase on increasing k but the computation cost also increases.

VII. System Model

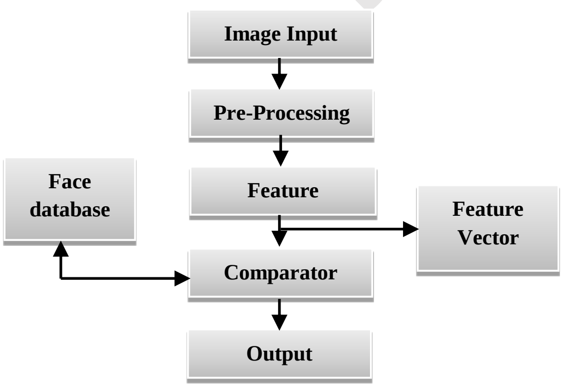

Figure 4: Basic flow diagram for face recognition

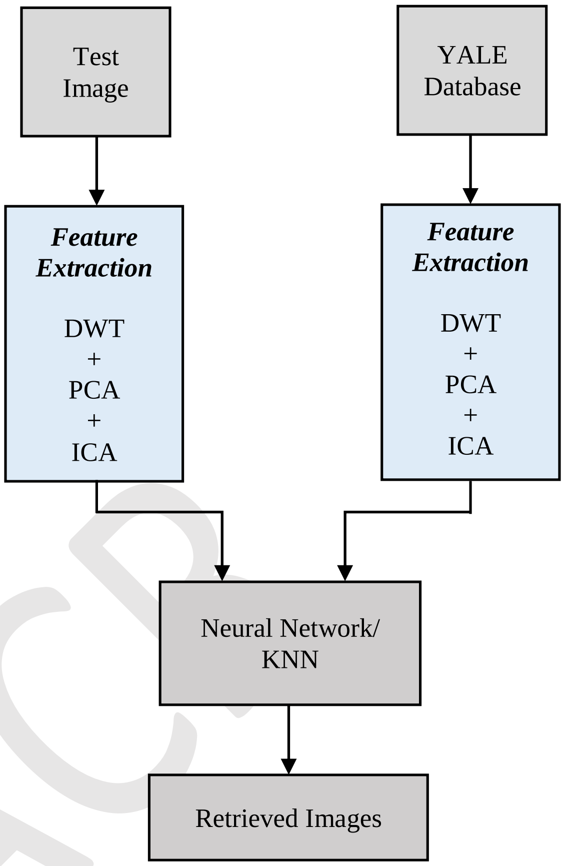

Figure 5: Block diagram for proposed approach

The proposed algorithm was tested in order to determine the performance and efficiency of the system. There were two stages in the process: the first is the training stage, done to obtain Eigen-faces of the database images and second is testing stage, done to test images of different orientations whether it match with the database images.

In addition, both stages have three steps:

- For each image presented above, wavelet decomposition was performed according to level (level 1, 2 and 4) to reduce the size of the original image and only the low-band wavelet was taken as the approximation image.
- Next, PCA was performed on this approximation image to obtain its Eigen-faces and were then stored in the database as training images.
- Eigen-faces of the testing and database images were compared to find the best match. System performance was measured in percentage considering the accuracy of matching images with those in the database. The accuracy of the system was measured based on the levels of the wavelet decomposition and the number of

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Eigen-faces that each image has in the database.

Feature Extraction

Now these transformed matrices are taken as input to the DWT. A wavelet function called "Haar" which is very simple and orthogonal is used in DWT [17]. In DWT, decomposition of matrices makes the output with four details, out of which most of the information in approximation details (smooth information), except the sharp edge information. To maintain the data efficient, instead of using all four sub bands the diagonal details which contain the sharp edge information is merged with approximation details.

The new modified/transformed with-in class and between-class scatter matrices are used for further procedure in PCA [18] for feature extraction. Finally a projection matrix with Eigen vectors [19] correspond to highest Eigen values [19] is obtained.

Classification:

Similarity measure is the step done after extracting features. The similarity between the test image and images in database can be obtained by simply measuring the distance. The distance is measured with Euclidian distance.

Data Acquisition:

In this paper we used the "Yale Face Database [20]. This database has 165 images of 15 individuals over different lighting conditions in 11 poses (all frontal pose, with different gesture and wearing glasses with 24∘ from the axis of the camera). In order to capture the images of this database,a geodesic lighting equipment with 64 Xenon strobes was constructed. A sample of images from this database can be seen in Figure 6.

Figure 6: Image samples

VIII. Simulation Results

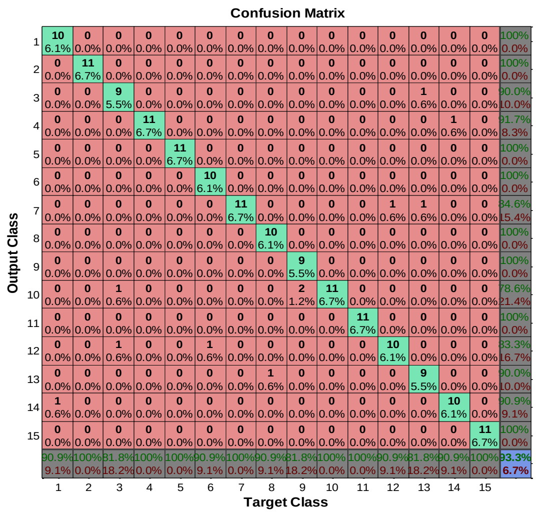

Figure 7: Confusion matrix plot for DWT-PCA-ICA-NN

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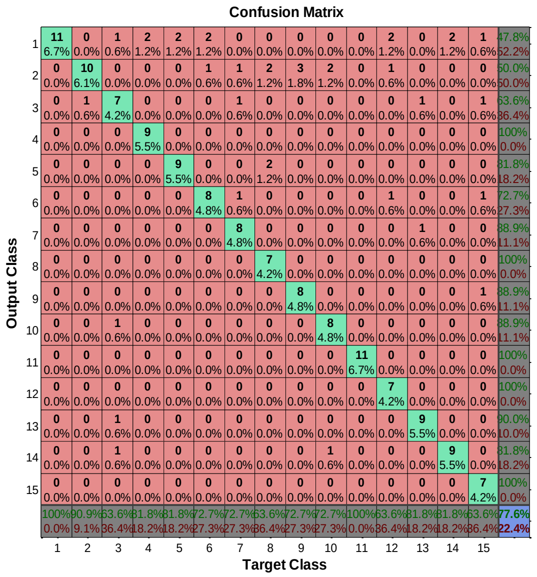

Figure 8: Confusion matrix plot for DWT-PCA-ICA-kNN

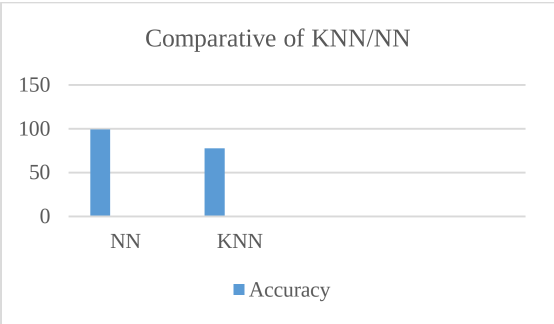

Figure 9: Comparative of KNN and NN

Table 1: Comparison for different method

Methods=K	Average Accuracy
DCT+KNN	60.34%
PCA+LDA+KNN	73.63
DWT+PCA+ICA+NN	93.6
DWT+PCA+ICA+KNN	77.78

IX. CONCLUSION

A number of different cases have been observed in this research work. The results shown here are obtained by using the Yale database [20] having 165 images with each image size of 100×100. The number of features is taken constant throughout all the methods. There are 15 persons, 11 images per each person. A hybrid technique of feature extraction of face recognition using DWT+PCA+ICA for robust and reliable face recognition system. In comparison with the k-NN, the proposed NN based method gives better recognition accuracy and discriminatory power; further, the proposed method reduces the computational load significantly when the image database is large.

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