# Study of Different Algorithms for Face Recognition

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BY
ANSHUMAN PRAKASH
ROLL NO: 10609031

And
MANOJ KUMAR TEWARI
ROLL NO: 10609023

Department of Electronics & Communication Engineering
National Institute of Technology, Rourkela

**National Institute of Technology Rourkela**

*Department of Electronics & Communication Engineering*

# CERTIFICATE

*This is to certify that the thesis titled,* ***"Study of Different Algorithms for Face Recognition"*** *submitted by Anshuman Prakash (Roll: 10609031) and Manoj Kumar Tewari (Roll: 10609023) in partial fulfilment of requirements for the award of* **Bachelors in Technology** *degree in Electronics and Communication Engineering in Department of Electronics and Communication Engineering at National Institute of Technology, Rourkela (Deemed University) is a bona fide work carried out by them under my supervision and guidance.*

Date: 10th May, 2010

**Dr. S.Meher**
Associate Professor

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**Anshuman Prakash**
Roll No: 10609031

**Manoj Kumar Tewari**
Roll No: 10609023

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# Abstract

The importance of utilising biometrics to establish personal authenticity and to detect impostors is growing in the present scenario of global security concern. Development of a biometric system for personal identification, which fulfils the requirements for access control of secured areas and other applications like identity validation for social welfare, crime detection, ATM access, computer security, etc., is felt to be the need of the day [2]. Face recognition has been evolving as a convenient biometric mode for human authentication for more than last two decades. It plays an important role in applications such as video surveillance, human computer interface, and face image database management [1]. A lot of techniques have been applied for different applications. Robustness and reliability becomes more and more important for these applications especially in security systems.

Basically Face Recognition is the process through which a person is identified by his facial image. With the help of this technique it is possible to use the facial image of a person to authenticate him into any secure system. Face recognition approaches for still images can be broadly categorized into holistic methods and feature based methods. Holistic methods use the entire raw face image as an input, whereas feature based methods extract local facial features and use their geometric and appearance properties.

This work studies the different approaches for a Face Recognition System. The different approaches like PCA, DCT and different types of Wavelets have been studied with the help of Euclidean distance as a classifier and Neural Network as a classifier.

The results have been compared for the two database, AMP which contains 975 images of 13 individuals (each person has 75 different images) under various facial expressions and lightning condition with each image being cropped and resized to 64×64 pixels for the simulation and ORL (Olivetti Research Lab) which contains 400 images (each with 112×92 pixels) corresponding to 40 persons in 10 poses each including both male and female. The ORL database image has been resized to 128×128 pixels.

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# Chapter 1

# Introduction

## 1.1 Background

Biometrics is a class of Pattern Recognition problem. Biometrics is automated method of identifying a person or verifying the identity of a person based on a physiological or behavioural characteristic. Examples of physiological characteristics include hand or finger images, facial characteristics. Biometric authentication requires comparing a registered or enrolled biometric sample (biometric template or identifier) against a newly captured biometric sample (for example, captured image during a login).

During enrolment, as shown in the figure below, a sample of the biometric trait is captured, processed by a computer, and stored for later comparison. Biometric recognition can be used in Identification mode, where the biometric system identifies a person from the entire enrolled population by searching a database for a match based solely on the biometric. Sometime identification is called "one-to-many" matching.

A system can also be used in Verification mode, where the biometric system authenticates a person's claimed identity from their previously enrolled pattern. This is also called "one-to-one" matching. In most computer access or network access environments, verification mode would be used.

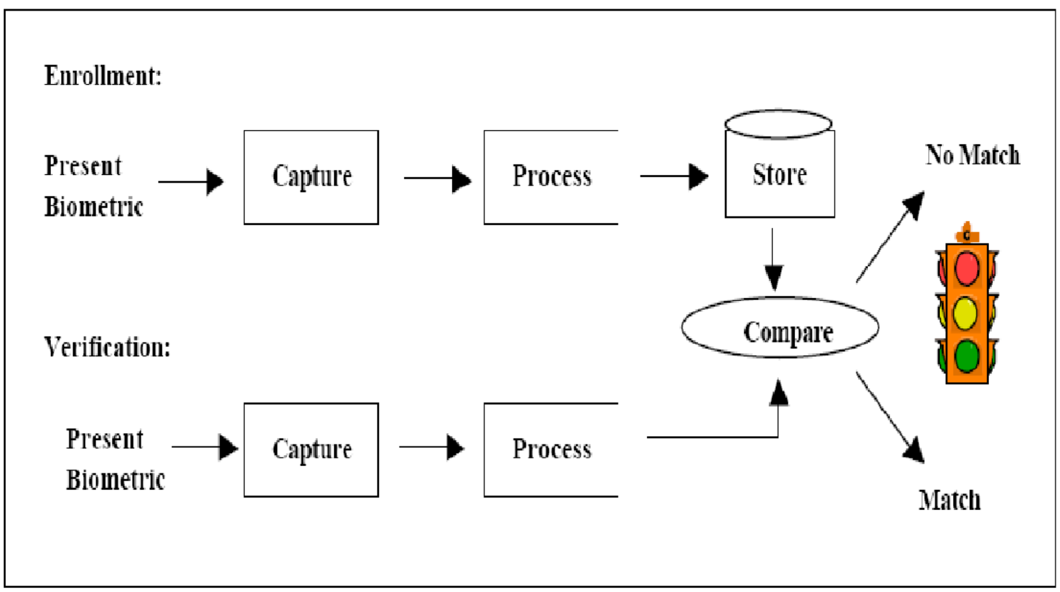



**Fig 1.1: A model of Face Recognition System**

## Face Recognition

The identification of a person by their facial images can be done in a number of different ways such as by capturing an image of the face in the visible spectrum using an inexpensive camera or by using the infrared patterns of facial heat emission. Facial Recognition in visible light typically model key features from the central portion of the facial image using a wide assortment of cameras in visible light system extract features from the captured images that do not change over time while avoiding superficial features such as facial expression or hair. Several approaches to model facial images in the visible spectrum are Principal Component Analysis (PCA), local feature analysis, Neural Network, multi-resolution analysis etc.

The challenges of facial recognition in the visible spectrum include reducing the impact of variable lightning and detecting a mask or photograph. Some facial recognition systems may require a stationary or posed user in order to capture image through many systems, though many systems use a real time process to detect a person's head and locate the face automatically. Major benefits of facial recognition are that it is non intrusive, hand free, continuous and accepted by most users.

Most research on face recognition falls into two main categories (Chellappa et al., 1995): feature-based and holistic. Geometric approaches dominated in the 1980's where simple measurements such as the distance between the eyes and shapes of lines connecting facial features were used to recognize faces, while holistic methods became very popular in the 1990's with the well known approach of Eigen-faces .

Feature-based approaches to face recognition basically rely on the detection and characterization of individual facial features and their geometrical relationships. Such features generally include the eyes, nose, and mouth. The detection of faces and their features prior to performing verification or recognition makes these approaches robust to positional variations of the faces in the input image.

Holistic or global approaches to face recognition, on the other hand, involve encoding the entire facial image and treating the resulting facial "code" as a point in a high-dimensional space. Thus, they assume that all faces are constrained to particular positions, orientations, and scales. Even though holistic methods such as neural networks are more complex to implement than their geometric counterparts, their application is much more straight forward, whereby an entire image segment can be reduced to a few key values for comparison with other stored key values and no exact measures or knowledge such as eye locations or the presence of moustaches needs to be known. The problem with this "grab all" approach was that noise, occlusions such as glasses and any other non face image attribute could be learned by the holistic algorithm and become part of the recognition result even though such factors are not unique to faces.

Feature-based approaches were more predominant in the early attempts at automating the process of face recognition. Some of this early work involved the use of very simple image processing techniques (such as edge detection, signatures, and so on) for detecting faces and their features (see, for example, Sakai et al., 1969; Kelly, 1970). In Sakai et al. (1969), an edge map was first extracted from an input image and then matched to a large oval template, with possible variations in position and size. The presence of a face was then confirmed by searching for edges at estimated locations of certain features like the eyes and mouth. Kelly (1970) used an improved edge detector involving heuristic planning to extract an accurate outline of a person's head from various backgrounds.

## 1.2 Motivation

Face Recognition as a concept has evolved over the years and it has been successfully used in various applications in biometric systems for more than last two decades. The importance of utilising biometrics to establish personal authenticity and to detect impostors has grown in the present scenario of global security concern. So there is a need for the development of a biometric system for personal identification, which fulfils the requirements for access control of secured areas and other applications like identity validation for social welfare, crime detection, ATM access, computer security, etc.

Variations in lighting conditions, pose and expression makes face recognition an even more challenging and difficult task.

A lot of techniques have been applied for different applications. Robustness and reliability becomes more and more important for these applications especially in security systems.

So in this work we have studied the different approaches to the Face Recognition via Discrete Cosine Transform (DCT), Principal Component Analysis and Wavelet Analysis and tried to compare the success rate of all the algorithms on two databases namely AMP and ORL (Olivetti Research Lab).

## 1.3 Achievements

In this work we have we have used Discrete Cosine Transform, Principal Component Analysis and Wavelet Theory for Face Recognition and tested the algorithms on two database. In the process following things were achieved:

a) We studied and tested the Face Recognition System based on Discrete Cosine Transform as described in [3]

b) We studied and tested the Face Recognition System based on Principal Component Analysis as described in [4],[5]

c) We studied and tested the different forms of Wavelets and applied it successfully for the Face Recognition as described in [6].

d) Both Euclidean distance classifier and Neural Network classifier were used.

# Chapter 2

# Face Recognition using Discrete Cosine Transform

## 2.1 Background

Data compression is very much essential for computer signal processing. Linear transforms play a very important role in the signal and image processing areas [3].

A transform is a mathematical operation which is applied to a signal that is being processed converting into different domain and then again is converted back to the original domain.

These transforms generate a set of coefficients from which it is possible to restore the original samples of the signal. A mathematical transform has an important property: when applied to a signal, i.e., they have the ability to generate decorrelated coefficients, concentrating most of the signal's energy in a reduced number of coefficients [7].

DCT is a very well known signal analysis tool used in compression standards due to its compact representation power. It has data independent nature. It is an invertible linear transform that expresses a finite sequence of data points in terms of a sum of cosine functions oscillating at different frequencies.

The DCT coefficients reflect the importance of frequencies that are present in it. The very first coefficient refers to the signal's lowest frequency and usually carries the majority of the relevant information from the original signal. The last coefficients refer to the signal's higher frequencies and these generally represent the more detailed or fine information of signal. The rest of the coefficients carry different information levels of the original signal. Since the DCT is related to the discrete Fourier transform (Rao and Yip, 1990), it can be computed efficiently. It is these properties of the DCT that we seek for face recognition.

## 2.2 Definition of DCT

Ahmed, Natarajan, and Rao (1974) first introduced the discrete cosine transform (DCT) in the early seventies. Ever since, the DCT has grown in popularity,
and several variants have been proposed (Rao and Yip, 1990). In particular, the DCT was categorized by Wang (1984) into four slightly different transformations named DCT-I, DCT-II, DCT-III, and DCT-IV [3].

Given an input sequence *u (n)* of length *N*, its DCT, *v (k)*, is obtained by the following equation:

$$v(k) = \alpha(k)\sum_{n=0}^{N-1} u(n)\cos\left(\frac{(2n+1)\pi k}{2N}\right) \qquad (2.1a)$$

$$0 \le k \le N-1$$

where

$$\alpha(0) = \sqrt{\frac{1}{N}}, \alpha(k) = \sqrt{\frac{2}{N}} \qquad (2.1b)$$

$$1 \le k \le N-1$$

Alternatively, we can think of the sequence *u (n)* as a vector and the DCT as a transformation matrix applied to this vector to obtain the output *v (k)*. In this case, the DCT transformation matrix, *C* = {*c (k, n)*}, is defined as follows:

$$c(k,n) = \begin{cases} \sqrt{\frac{1}{N}} k = 0, 0 \le n \le N-1 \\ \sqrt{\frac{2}{N}}\cos\left(\frac{(2n+1)\pi k}{2N}\right) 1 \le k \le N-1, 0 \le n \le N-1 \end{cases} \qquad (2.2)$$

where *k* and *n* are the row and column indices, respectively.

Using Eq. (2.2), the DCT of the sequence *u (n)* (or vector **u**) is simply

$$\mathbf{v} = C\mathbf{u} \qquad (2.3)$$

The inverse discrete cosine transform permits us to obtain *u (n)* from *v (k)*. It is defined by:

$$u(n) = \sum_{n=0}^{N-1} \alpha(k)v(k)\cos\left(\frac{(2n+1)\pi k}{2N}\right) \qquad (2.4)$$

$$0 \le n \le N-1$$

with *α(k)* as given in Eq. (2.1b). Using Eq. (2.3), the inverse discrete cosine transform, **u**, of a vector **v** is obtained by applying the inverse of matrix *C* to **v**. That is, the inverse discrete cosine transform is found from

$$u = C^{-1} v \tag{2.5}$$

From these definitions, we observe that by applying the discrete cosine transform to an input sequence, we simply decompose it into a weighted sum of basis cosine sequences. This is obvious from Eq. (2.4) in which *u (n)* is reconstructed by a summation of cosines which are weighted by the DCT coefficients obtained from Eq. (2.1) or (2.3). These basis sequences of the
DCT are the rows of the matrix *C*.

## 2.3 Basic Algorithm

The basic Face Recognition Algorithm is discussed below as depicted in Fig: 2.1. Both normalization and recognition are involved in it. As can be seen from Fig. 2.1, the system receives as input an image containing a face .The normalized (and cropped) face is obtained and then it can be compared to other faces, under the same nominal size, orientation, position, and illumination conditions. This comparison is based on features extracted using the DCT. The basic idea here is to compute the DCT of the normalized face and retain a certain subset of the DCT coefficients as a feature vector describing this face.

This feature vector contains the low-to-mid frequency DCT coefficients, as these are the ones having the highest variance and contain the maximum information.

For recognizing a particular input face, the system compares the face's feature vector to the feature vectors of the database faces using a Euclidean distance nearest-neighbour classifier (Duda and Hart, 1973).

If the feature vector of the probe is **v** and that of a database face is **f**, then the Euclidean distance between the two is

$$d = \sqrt{(f_0 - v_0)^2 + (f_1 - v_1)^2 + ........... + (f_{M-1} - v_{M-1})^2}$$

where

$$v = [v_0, v_1, ..........v_{M-1}]^T$$
$$f = [f_0, f_1, ..........f_{M-1}]^T$$

and *M* is the number of DCT coefficients retained as features. A match is obtained by minimizing *d*.

This approach computes the DCT on the entire normalized image. This is different from the use of the DCT in the JPEG compression standard (Pennebaker and Mitchell, 1993), in which the DCT is computed on individual subsets of the image.
So in this approach we haven't assumed any threshold on $d$. So the system described always assumes that the closest match is the correct match, and no probe is ever rejected as unknown.

If a threshold $q$ is defined on $d$, then the gallery face that minimizes $d$ would only be output as the match when $d < q$. Otherwise, the probe would be declared as unknown. In this way, we can actually define a threshold to achieve 100% recognition accuracy, but, of course, at the cost of a certain number of rejections.

In other words, the system could end up declaring an input face as unknown even though it exists in the gallery. Suitable values of $q$ can be obtained using the so-called Receiver Operating Characteristic curve (ROC).

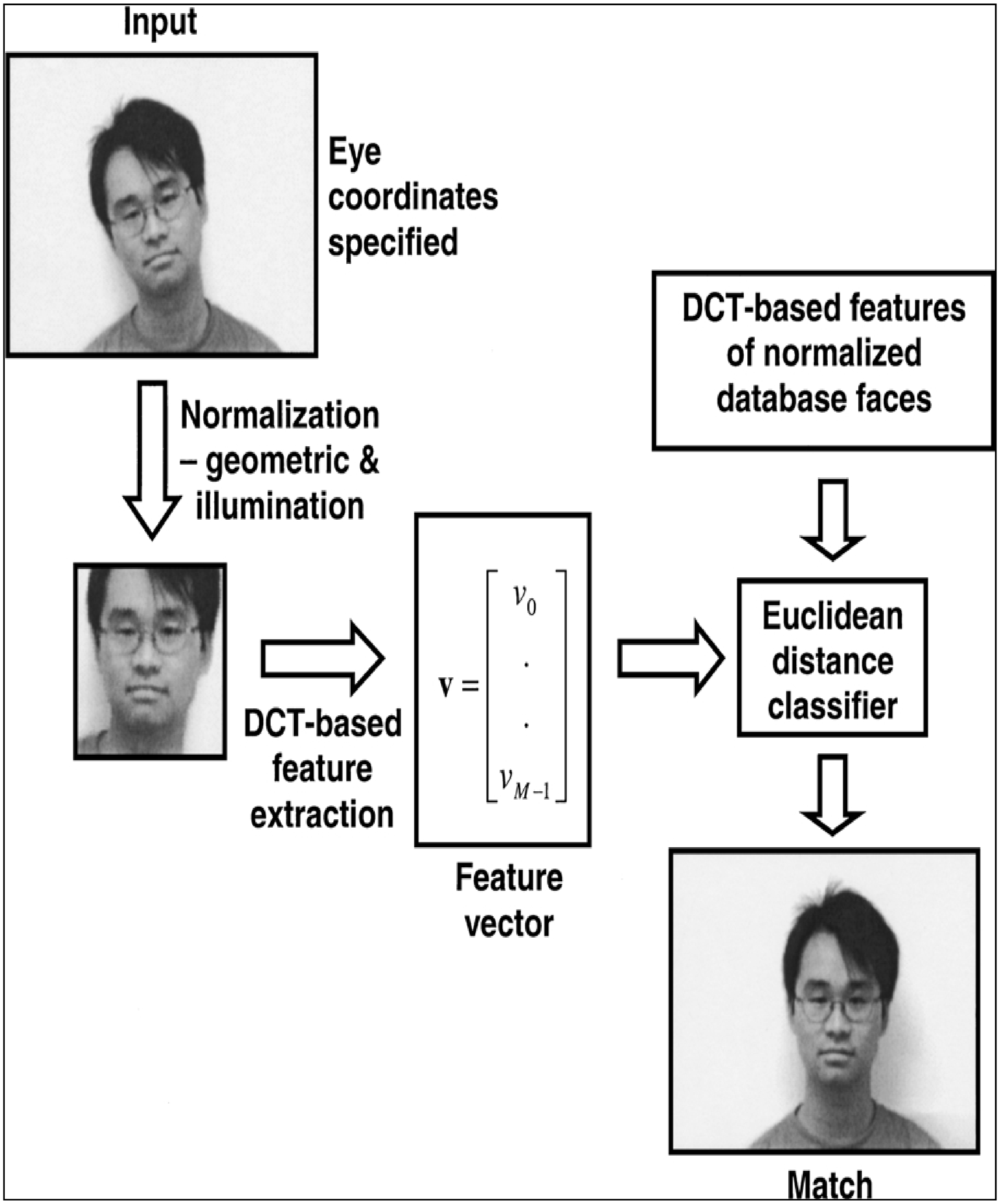



**Fig 2.1: DCT Based Face Recognition System**

### 2.3.1 Feature Extraction

The features are extracted with the help of DCT. So the DCT is computed for obtaining the feature vector representing a face and only a subset of the obtained coefficients is retained.

The size of this subset is chosen such that it can sufficiently represent a face. It is observed that the DCT coefficients exhibit the expected behaviour in which a relatively large amount of information about the original image is stored in a fairly small number of coefficients. Most of the discarded coefficients have magnitudes less than 1.

So the main concept taken into account by the proposed feature selection stage is that low frequency DCT coefficients do concentrate more energy than others. Also it is not true that these high amplitude coefficients are always located in the lower part of the spectrum.

The database which we have used, there is no need of pre-processing. In this way we have reduced the computational complexity. So direct DCT based features are extracted.

We have used two database, AMP which contains 975 images of 13 individuals (each person has 75 different images) under various facial expressions and lightning condition with each image being cropped and resized to 64×64 pixels for the simulation and ORL (Olivetti Research Lab) which contains 400 images (each with 112×92 pixels) corresponding to 40 persons in 10 poses each including both male and female. The ORL database image has been resized to 128×128 pixels.

All the images are taken against a dark homogeneous background, little variation of illumination, slightly different facial expression and details (open/close eyes, smiling/non smiling, glasses/no glasses etc.)

### 2.3.1.1 Euclidean Distance Classifier

As in AMP database there is less pose variation, so we are taking only 6-10 number of lower frequency components while for ORL 150 DCT coefficients are taken as there is very large variation. .

Above approach used in the selection of DCT coefficients is fast and simple.

### 2.3.1.2 Neural Network Classifier

Neural Network Classifier is used only for the AMP database. For training purpose 20 face samples from each class is taken. For each face we are taking 15 low frequency DCT coefficients.

## 2.3.2 Testing

The testing was done as described in the Fig 2.2. Euclidean distance classifier as well as Neural Network classifier was used for the database AMP while for the ORL database only Euclidean distance was used.

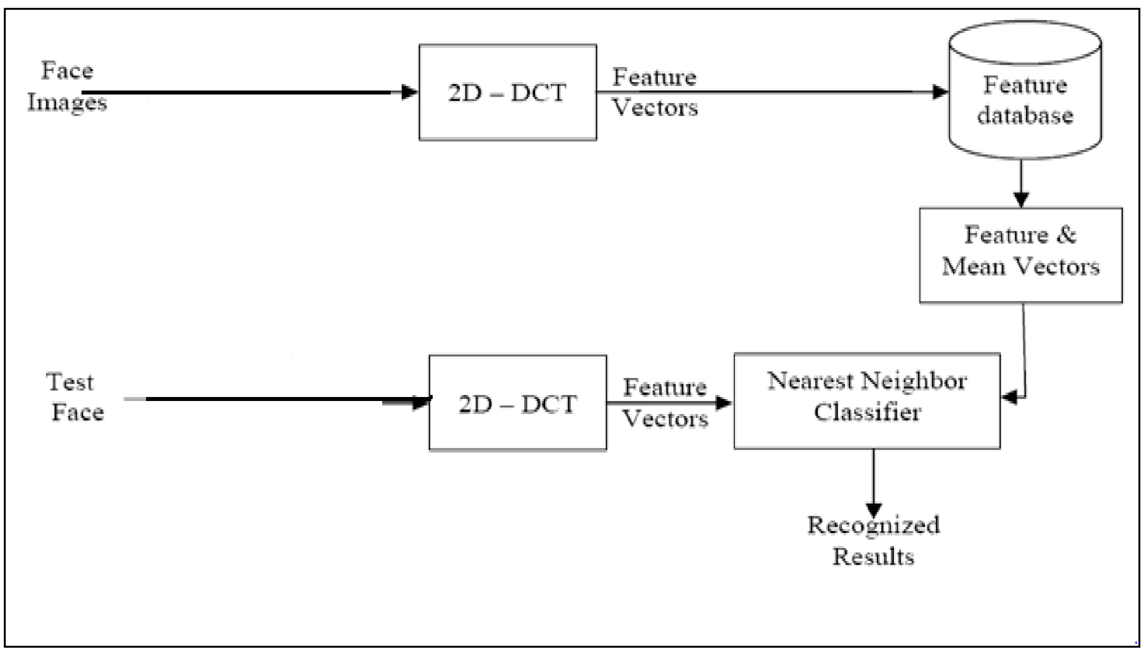



**Fig 2.2: Face Recognition System using DCT & Euclidean Distance Classifier**

The testing was also done using Neural Network as a classifier.

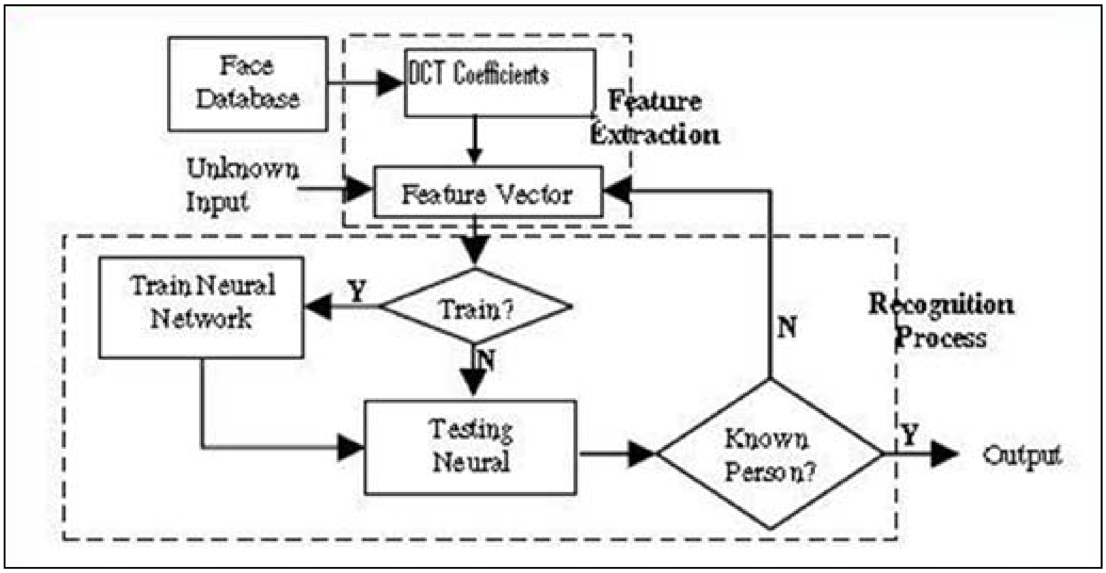



**Fig: 2.3 Face Recognition System using DCT & MLNN**

## 2.3.3 Experimental Set up

## 2.3.3.1 Euclidean Distance Classifier

The whole experiment was done with the help of the database AMP & ORL. AMP contains 975 images of 13 individuals(each person has 75 different images) under various facial expressions and lightning condition with each image being cropped and resized to 64×64 pixels for the simulation.

ORL (Olivetti Research Lab) contains 400 images (each with 112×92 pixels) corresponding to 40 persons in 10 poses each including both male and female. The ORL database image has been resized to 128×128 pixels.
For AMP database 6-10 DCT coefficients were used while for ORL 150 DCT coefficients were used.

For each and every person, the number of training faces has been varied from 1 to 9 and correspondingly, the number of test faces from 74 to 64.

### 2.3.3.2 Neural Network Classifier

Neural Network classifier is used only for AMP database. For training purpose, 20 face samples are taken for each class.15 low frequency DCT coefficients are taken for each face. 20, 10, 1 number of neurons are taken in the input, hidden and output layer of the MLNN. The activation functions used are tan sigmoid, log sigmoid and purely linear in the input, hidden and output layer respectively. The training of the MLNN is done with the help of simple back-propagation algorithm .The stopping criteria for stopping the training is the level of MSE is 1e-10 or 5000 number of epochs whatever occurs first.

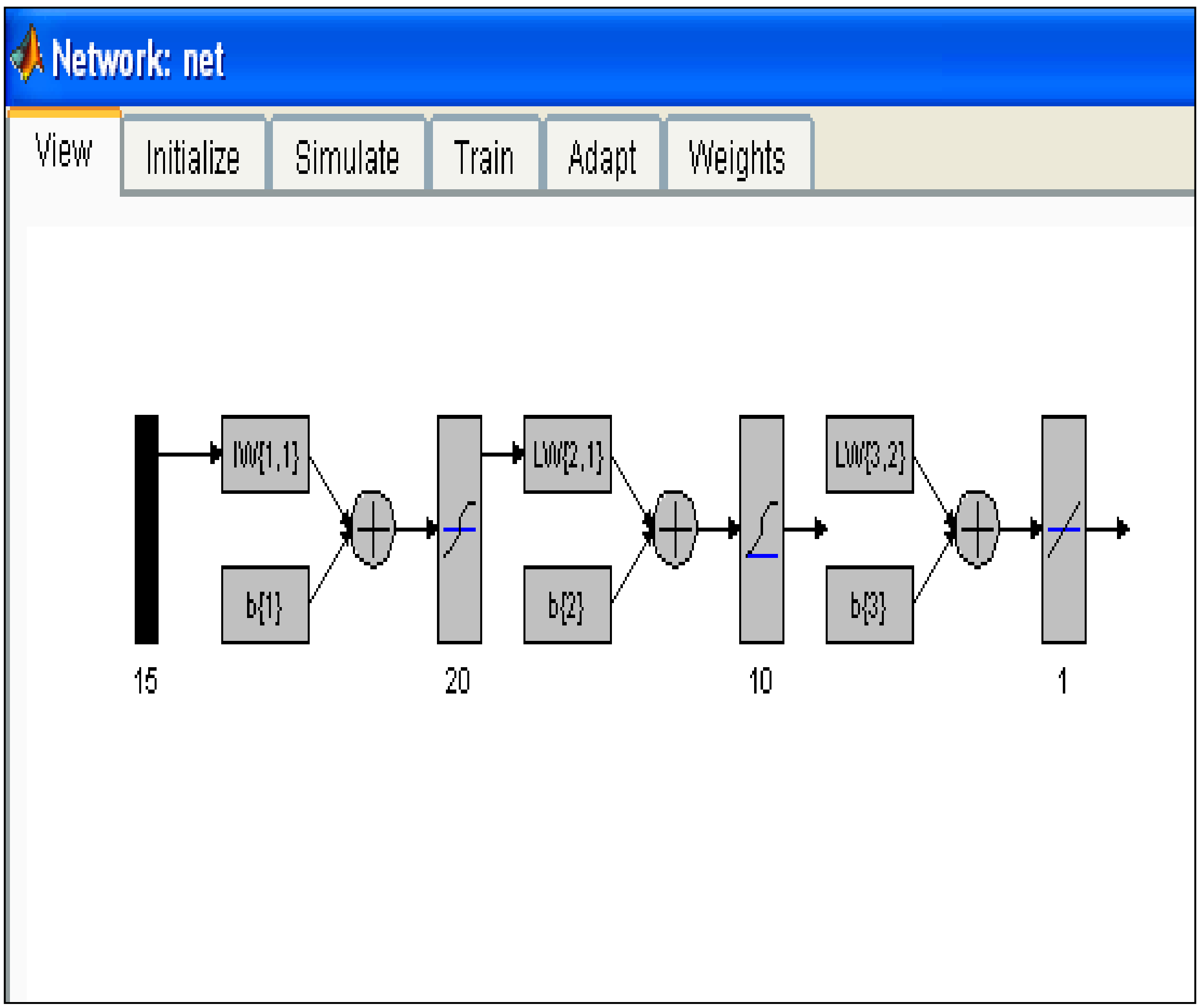



**Fig:2.4 Structure of used Multi Layer Perceptron Network**

**Fig 2.5: Views included in the AMP database**

**Fig 2.6: Views included in ORL Database**

## 2.3.4 Experimental Results

For each and every person in the AMP database, the number of training faces, number of testing faces and number of testing faces recognized successfully is tabulated as shown below.

**Table No: 2.1**

| Training Faces | Testing Faces | Number of testing faces recognized successfully for 13 persons | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | A | B | C | D | E | F | G | H | I | J | K | L | M |
| 1 | 74 | 74 | 54 | 74 | 47 | 64 | 71 | 74 | 74 | 74 | 74 | 74 | 74 | 74 |
| 2 | 73 | 73 | 47 | 73 | 47 | 73 | 73 | 73 | 73 | 73 | 73 | 73 | 73 | 73 |
| 3 | 72 | 72 | 61 | 72 | 64 | 72 | 72 | 72 | 72 | 72 | 72 | 72 | 72 | 72 |
| 4 | 71 | 71 | 67 | 71 | 66 | 67 | 71 | 71 | 71 | 71 | 71 | 71 | 71 | 71 |
| 5 | 70 | 70 | 68 | 70 | 68 | 67 | 70 | 70 | 70 | 70 | 70 | 70 | 70 | 70 |
| 6 | 69 | 69 | 67 | 69 | 66 | 68 | 69 | 69 | 69 | 69 | 69 | 69 | 69 | 69 |
| 7 | 68 | 68 | 62 | 68 | 63 | 65 | 68 | 68 | 68 | 68 | 68 | 68 | 68 | 68 |
| 8 | 67 | 67 | 51 | 67 | 61 | 63 | 67 | 67 | 67 | 67 | 67 | 67 | 67 | 67 |
| 9 | 66 | 66 | 50 | 66 | 58 | 62 | 66 | 66 | 66 | 66 | 66 | 66 | 66 | 66 |

The overall success rate for the AMP database by taking different number of training and testing faces is tabulated below:

**Table No: 2.2**

| No. of Training Faces | No. of Testing Faces | Overall Success Percentage |
|---|---|---|
| 1 | 74 | 93.6590 |
| 2 | 73 | 92.5205 |
| 3 | 72 | 95.9701 |
| 4 | 71 | 98.5915 |
| 5 | 70 | 99.2308 |
| 6 | 69 | 99.3311 |
| 7 | 68 | 98.4163 |
| 8 | 67 | 95.0149 |
| 9 | 66 | 94.7366 |

The overall success rate for the AMP database by taking different number of training and testing faces is tabulated below:

**Table No: 2.3**

| No. of Training Faces | No. of Testing Faces | Success percentage |
|---|---|---|
| 1 | 9 | 55.5000 |
| 2 | 8 | 62.5000 |
| 3 | 7 | 63.5714 |
| 4 | 6 | 62.5833 |
| 5 | 5 | 62.5000 |
| 6 | 4 | 64.8750 |
| 7 | 3 | 63.0000 |
| 8 | 2 | 65.5000 |
| 9 | 1 | 82.5000 |

The simulation was also run by varying the number of DCT coefficients as well as the number of training faces. The results obtained is as shown below:

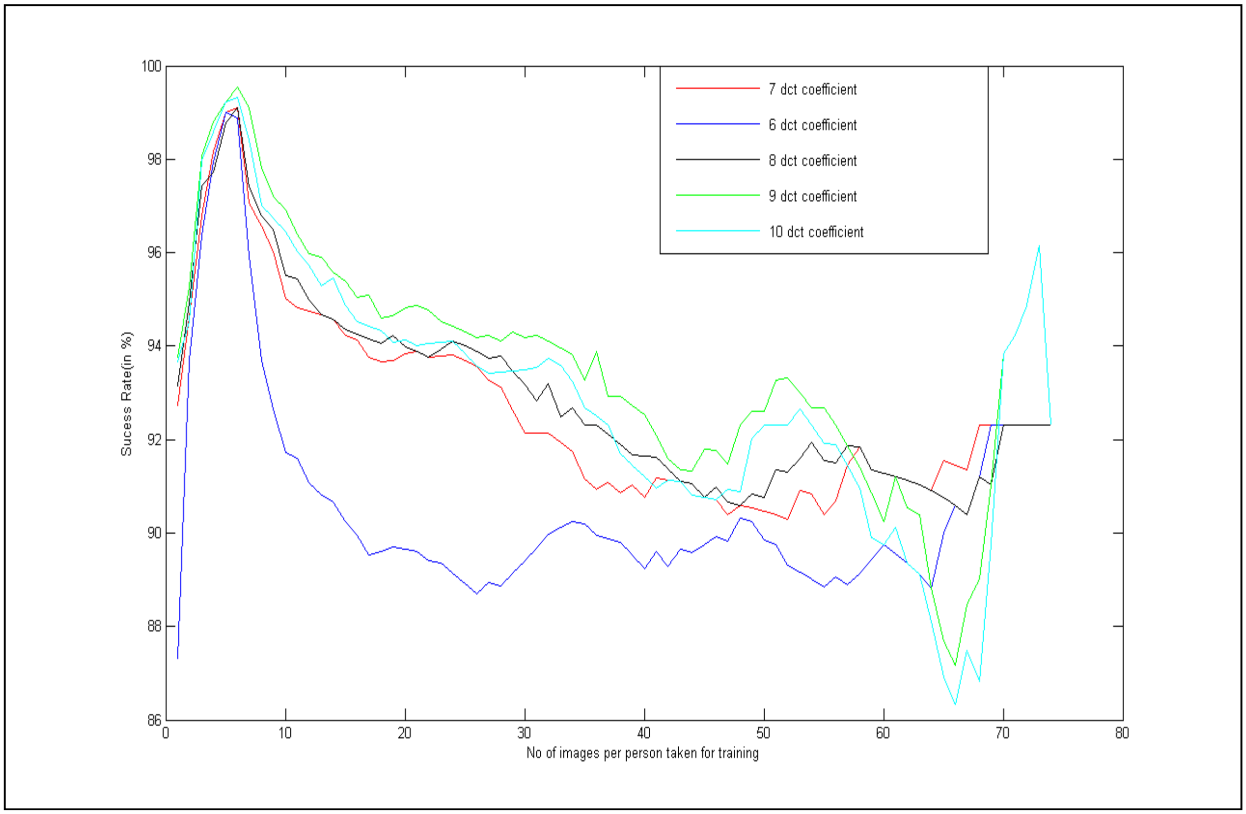



**Fig 2.7: Performance of DCT based face recognition with AMP face database**

The result for the Neural Network Classifier used for the AMP database is as shown below:

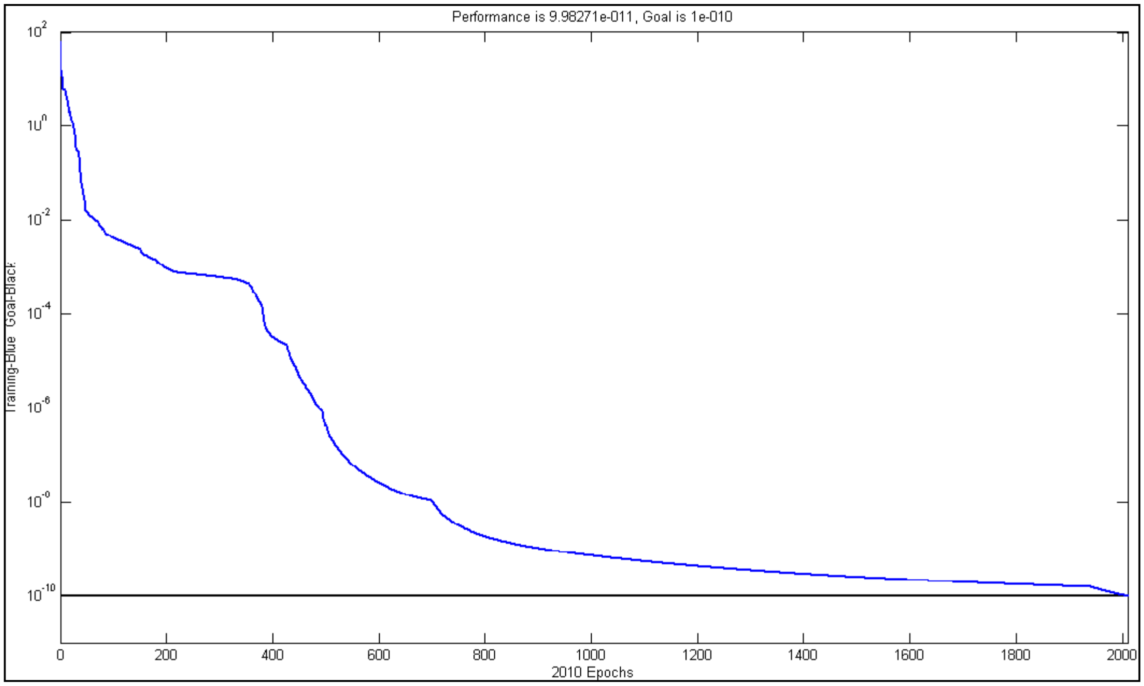



**Fig 2.8: Mean Square Error plot for used MLNN**

The stopping criteria for stopping the training is the level of MSE is 1e-10 or 5000 number of epochs whatever occur first. The recognition rate which we are getting is around 98.18%.

## 2.4 Conclusion

It is clear from table 2.2 that DCT based face recognition system performs well when there are less pose and illumination variations. This table was created for AMP face data base, in which very less pose variations were there. So DCT based recognition system is giving success rate around 99%.But for ORL face data base ,the Table 2.3 shows success rate to be around 82%.The reason is clear for less success rate with this face data base. In ORL face data base there are large pose variations. So DCT based recognition system is not giving high success rate. So from the above discussion, we can conclude that though DCT based recognition system is simple, but is not suitable for the conditions where there are large pose or illumination variations.

# Chapter 3

# Face Recognition using Principal Component Analysis

## 3.1 Background

PCA is a statistical dimensionality reduction method, which produces the optimal linear squares decomposition of a training set. It reduces the dimensionality of a data set while retaining the majority of the variation present in the data set (Jolliffe 1986).

It has been successfully used in Face Recognition systems. In the case of Face Recognition system based on PCA, it seeks to capture the variation in a collection of face images and use this information to encode and compare images of individual faces in a holistic manner. Eigen- face Method is verified well for the recognition strategy and in controlled condition.

An image space can be considered as a space having dimensions equal to the number of pixels making up the image and having values in the range of the pixels values and an image can be thought as a point in the image space by converting the image to a long vector by concatenating each column of the image one after the other [4].

When all the face images are converted into vectors, they will group at a certain location in the image space as they have similar structure, having eye, nose and mouth in common and their relative position correlated. This correlation is the main point to start the Eigen-face analysis.

The Eigen-face method tries to find a lower dimensional space for the representation of the face images by eliminating the variance due to non-face images; that is, it tries to focus on the variation just coming out of the variation between the face images. So Eigen-face method aims to build a face space which better describes the faces. The basis vectors of this face space are called the principal component and the Eigen-face method is the implementation of Principal Component Analysis (PCA) over images.

## 3.2 Eigen-faces for Recognition

In the language of Information theory, we want to extract the relevant information in a face image, encoding with a database of models encoded similarly as efficiently as possible, and compare one face encoding with a database of models, encoded similarly. So, mathematically we wish to find the principal components of the distribution of faces, or the Eigen-vectors of the covariance matrix of the set of face images.

A simple approach to extract the information contained in an image of a face is to somehow capture the variation in a collection of face images, independent of any judgment of features, and use this information to encode and compare individual face images.

In mathematical terms, Eigen-face method finds the principal components of the distribution of faces, or the Eigen-vectors of the covariance matrix of the set of face images, treats an image as point (or vector) in a very high dimensional space. The Eigen-vectors are ordered, each one accounting for a different amount of the variation among the face images [5].

These Eigen-vectors can be thought of as a set of features that together characterize the variation between face images. Each image location contributes more or less to each Eigen-vector, so that we can display the Eigen-vector as a sort of ghostly face which is why we call this by Eigen-face. Each Eigen-face deviates from uniform gray where some facial feature differs among the set of training faces; they are a sort of map of the variations between faces. Each individual face can be represented exactly in terms of a linear combination of the Eigen-faces.

The number of possible Eigen-faces is equal to the number of face images in the training set. However we can also represent the faces by approximating these by the best Eigen-faces having largest Eigen-values which in turn account for the most variance within the set of face images. This increases the computational efficiency.

The following steps are involved in the recognition process [5]:

1) Initialization: The training set of face images is acquired and Eigen-faces are calculated which define the face space.
2) When a new face is encountered, a set of weights based on input image and M Eigen-faces is calculated by projecting the input image onto each of the Eigen-faces.
3) The image is determined to be face or not by checking if it is sufficiently close to face space.
4) If it is a face, the weight patterns are classified as either a known person or an unknown one.

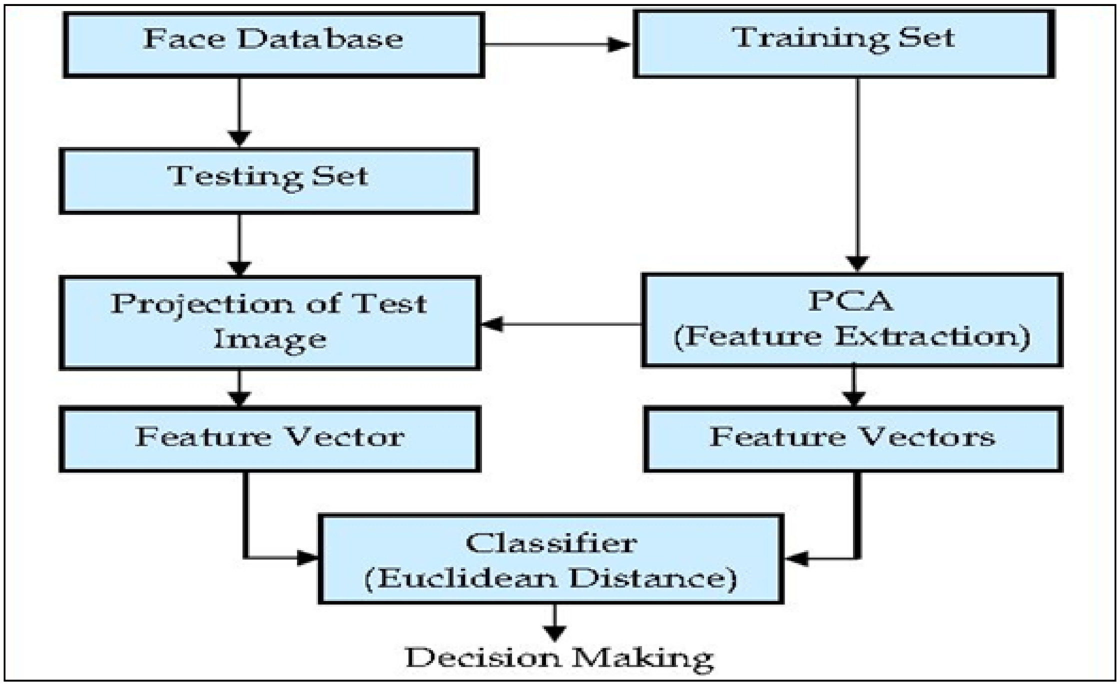



**Fig 3.1: Face Recognition System using PCA**

## 3.2.1 Calculating Eigen-faces

Since the images of faces are similar in overall configuration, they are not randomly distributed in the image space and thus are described by a relatively low dimensional subspace. The main idea of the PCA is to find the vectors which best account for the distribution of face images within the entire image space [4].

Mathematically, let the image be denoted by I.

Image I: (N x N) pixels (3.1)

Now the image matrix I of size (N x N) pixels is converted to the image vector Γ of size (P x 1) where P = (N x N); that is the image matrix is reconstructed by adding each column one after the other.

Let the training set be denoted by Γ

Training Set: $\Gamma = [\Gamma_1\ \Gamma_2\ ...\ \Gamma_M]$ (3.2)

is the training set of image vectors and its size is (P x M ) where M is the number of the training images.

Now the Mean face is calculated by the equation:

Mean Face: $\Psi = \frac{1}{M}\sum_{i=1}^{i=M} \Gamma\, i$ (3.3)

is the arithmetic average of the training image vectors at each pixel point and its size is P×1.

Mean Subtracted Image: $\Phi = \Gamma - \Psi$ (3.4)

is the difference of the training image from the mean image.

Difference Matrix: $A = [\Phi_1\ \Phi_2 \ldots \Phi_M\ ]$ (3.5)

is the matrix of all the mean subtracted training image vectors and its size is (P×M).

Covariance Matrix: $X = A \cdot A^T = \frac{1}{M}\sum_{i=1}^{M} \phi_i \phi_i^T$ (3.6)

is the covariance matrix of the training image vectors of size (P×P).

An important property of the Eigen-face method is obtaining the Eigen-vectors of the covariance matrix. For a face image of size (N x N) pixels, the covariance matrix is of size (P x P), P being (N x N). This covariance matrix is very hard to work with due to its huge dimension causing computational complexity.

On the other hand, Eigen-face method calculates the Eigen-vectors of the (M x M) matrix, M being the number of face images, and obtains (P x P) matrix using the Eigen-vectors of the (M x M) matrix.

Initially, a matrix Y is defined as,

$Y = A^T . A = \frac{1}{M}\sum_{i=1}^{M} \Gamma_i \Gamma_i^T$ (3.7)

which is of size (M×M) .

Then the Eigen-vectors $v_i$ and Eigen-values $\mu_i$ are obtained,

$Y. v_i = \mu_i . v_i$ (3.8)

The value of Y is put in this equation,

$$A^T.A\ .v_i = \mu_i\ .v_i \tag{3.9}$$

Now both the sides are multiplied by A on left side,

$$A.\ A^T.A.v_i = A.\ \mu_i\ .v_i \tag{3.10}$$

which can be represented as

$$A.\ A^T.A\ .v_i = \mu_i\ .A.v_i \tag{3.11}$$

$$X\ .A.v_i = \mu_i\ .A.v_i \tag{3.12}$$

Now let us group $A.v_i$ and call it $\upsilon_i$

It is now easily seen that

$$\upsilon_i = A.\ v_i \tag{3.13}$$

is one of the Eigen-vectors of $X= A.A^T$

Thus, it is possible to obtain the Eigen-vectors of X by using the Eigen-vectors of Y. A matrix of size (M x M) is utilized instead of a matrix of size (P x P) (i.e. [{N x N} x {N x N}]). This formulation brings substantial computational efficiency.

In Figure 3.3, some example images and mean image of the images from the AMP database are given. In Figure 3.3, some characteristic Eigen-faces obtained from this database can be seen. The Eigen-faces are in fact (P x 1) vectors for the computations; in order to see what they look like, they are rearranged as (N x N) matrices.

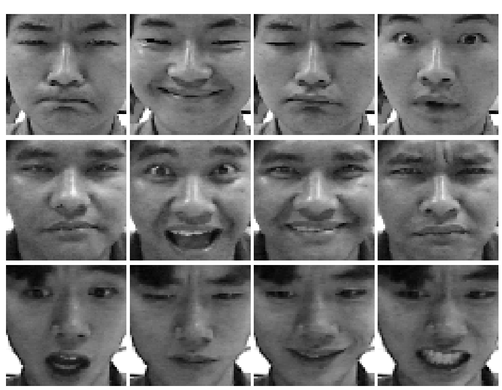


**Fig 3.2: Training faces from AMP face database**

**Fig 3.3: Mean training face**

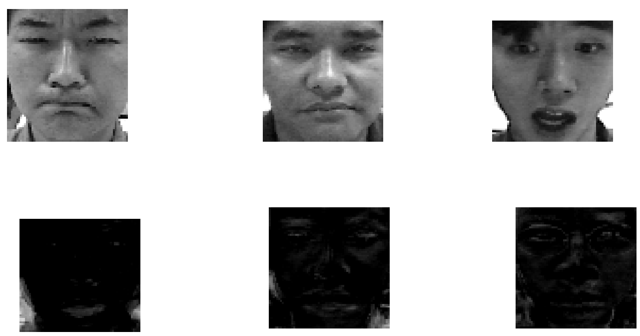


**Fig 3.4: Eigen-faces**

Instead of using M of the Eigen-faces, M'≤ M of the Eigen-faces can be used for the Eigen-face projection. This is achieved to eliminate some of the Eigen-vectors with small Eigen-values, which contribute less variance in the data.

In the next step, the training images are projected into the Eigen-face space and thus the weight of each eigenvector to represent the image in the Eigen-face space is calculated. This weight is simply the dot product of each image with each of the Eigen-vectors.

Projection: $w_k = v_k$ (3.14)

is the projection of a training image on each of the Eigen-vectors where k=1,2,3,.... M′

Weight Matrix: $\Omega = [w_1 \; w2 \; \ldots \; w_{M'}]^T$ (3.15)

is the representation of the training image in the Eigen-face space and its size is M×1.

So the images are just composed of weights in the Eigen-face space, simply like they have pixel values in the image space. The important aspect of the Eigen-face transform lies in this property. Each image is represented by an image of size (N x N) in the image space, whereas the same image is represented by a vector of size (M′ x 1) in the Eigen-face space. Moreover, having the dimension structure related to the variance of the data in hand makes the Eigen-face representation a generalized representation of the data.

This makes the algorithm a solution to the curse of dimensionality problem.

## 3.2.2 Classification of test image

For the classification of a new test image, it is also mean subtracted first and projected onto the Eigen-face space and then Nearest Mean algorithm [10] is used for the classification of the test image vector in the standard Eigen-face method; that is, the test image is assumed to belong to the nearest class by calculating the Euclidean distance of the test image vector to the mean of each class of the training image vectors.

Test image vector: $\Gamma_T$ (3.16)

is the test image vector of size P×1.

Mean subtracted image: $\Phi = \Gamma_T - \Psi$ (3.17)

is the difference of the test image from the mean image of size P×1.

Projection $= v_k{}^T \cdot \Phi = v_k{}^T \cdot (\Gamma - \Psi)^T$ (3.18)

is the projection of a training image on each of the Eigen-vectors where k=1,2,3,... M′

Weight Matrix: $\Omega_T = [w_1 \;\; w_2 \;\; \ldots \;\; w_{M'}\,]^T$ (3.19)

is the representation of the test image in the Eigen-face space and its size is
(M′ x 1).

A similarity measure is defined as the Euclidean distance between the test image vector and $i^{th}$ face class.

## 3.3 Experimental Set up

The whole experiment was done with the help of the database AMP & ORL. AMP contains 975 images of 13 individuals(each person has 75 different images) under various facial expressions and lightning condition with each image being cropped and resized to 64×64 pixels for the simulation.

ORL (Olivetti Research Lab) contains 400 images (each with 112×92 pixels) corresponding to 40 persons in 10 poses each including both male and female. The ORL database image has been resized to 128×128 pixels.

## 3.4 Experimental Results

For the AMP database, testing is done both by varying the number of the training face per class and the used Eigen-faces. The result is tabulated as shown in the Table 3.1.

**Table 3.1**

| No of Training Faces | No of Eigen Faces | Success Rate | No of Training Faces | No of Eigen Faces | Success Rate |
|---|---|---|---|---|---|
| 1 | 4 | 30.7692 | 4 | 43 | 82.6154 |
| | 5 | 38.2536 | | 44 | 82.6154 |
| | 6 | 44.0499 | | 45 | 92.3077 |
| | 7 | 53.7422 | | 46 | 92.3077 |
| | 8 | 61.4345 | | 47 | 92.3077 |
| | 9 | 65.6715 | | 48 | 92.3077 |
| | 10 | 73.3638 | | 49 | 100 |
| | 11 | 83.1601 | | 50 | 100 |
| | 12 | 90.8524 | | 51 | 100 |
| | 13 | 98.5447 | | 52 | 100 |
| 2 | 17 | 69.2308 | 5 | 56 | 92.3077 |
| | 18 | 69.2308 | | 57 | 92.3077 |
| | 19 | 74.9231 | | 58 | 92.3077 |
| | 20 | 74.9231 | | 59 | 92.3077 |
| | 21 | 82.5100 | | 60 | 92.3077 |
| | 22 | 82.5100 | | 61 | 100 |
| | 23 | 92.2023 | | 62 | 100 |
| | 24 | 92.3077 | | 63 | 100 |
| | 25 | 100 | | 64 | 100 |
| | 26 | 100 | | 65 | 100 |
| 3 | 30 | 74.9231 | 6 | 69 | 92.3077 |
| | 31 | 82.6154 | | 70 | 92.3077 |
| | 32 | 82.6154 | | 71 | 92.3077 |
| | 33 | 82.6154 | | 72 | 92.3077 |
| | 34 | 92.3077 | | 73 | 92.3077 |
| | 35 | 92.3077 | | 74 | 100 |
| | 36 | 92.3077 | | 75 | 100 |
| | 37 | 100 | | 76 | 100 |
| | 38 | 100 | | 77 | 100 |
| | 39 | 100 | | 78 | 100 |

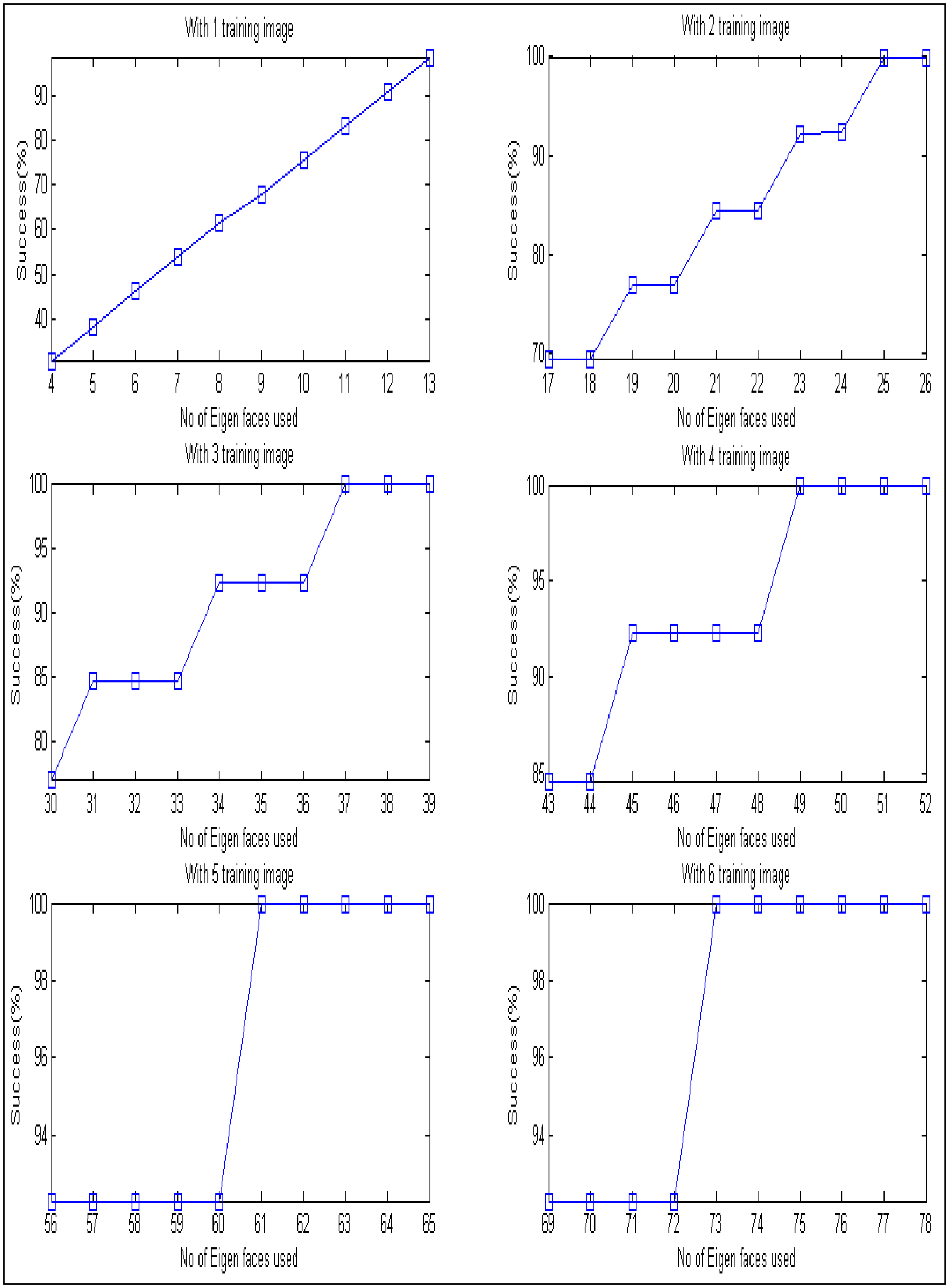



**Fig 3.5: Performance of PCA based face recognition with AMP face database**

For the ORL database, testing is done both by varying the number of the training face per class. The result is tabulated as shown in the Table 3.2.

**Table 3.2**

| No. of Training Faces | No. of Testing faces | Overall Success Rate |
|---|---|---|
| 1 | 9 | 61.9444 |
| 2 | 8 | 70 |
| 3 | 7 | 72.8571 |
| 4 | 6 | 74.6667 |
| 5 | 5 | 78 |
| 6 | 4 | 89.3750 |
| 7 | 3 | 91.6667 |
| 8 | 2 | 93.7500 |
| 9 | 1 | 95 |

## 3.5 Conclusion

PCA is basically a technique to represent the feature vector in the lower dimensionality space. So, by considering all the pixel values of image as the feature vector, we are getting better representation of image. That is why this technique is working better than DCT based technique even in large pose and illumination variations. This is evident from the results shown for both AMP face database as well as for ORL database in Table 3.1 and Table 3.2 respectively.

So PCA based face recognition system is appropriate for both types of database ,one having less variations and the other having large variations. But the problem is the complexity of the PCA based system.

# Chapter 4

# Face Recognition using Wavelet

## 4.1 Background

Wavelet provides powerful signal analysis tools, which is widely used in feature extraction, image compression and de-noising applications. Wavelet decomposition is the most widely used multi-resolution technique in image processing. Due to the excellent time-frequency localization characteristic, Wavelet transform provide a powerful signal analysis tools [19]. Images have typically locally varying statistics that result from different combinations of abrupt features like edges, of textured regions and of relatively low-contrast homogeneous regions. While such variability and spatial non-stationary defies any single statistical characterization, the multi-resolution components are more easily handled. Wavelet transform can be performed for every scale and translation, resulting in continuous wavelet transforms (CWT), or only at multiples of scale and translation intervals, resulting in discrete wavelet transform (DWT). Since, CWT provides redundant information and requires a lot of computation, generally DWT is preferred. The two-dimensional wavelet transform is performed by consecutively applying one-dimensional wavelet transform to the rows and columns of the two-dimensional data [6].

## 4.2 Definition of Wavelet

Let h and g be the Wavelet decomposition (analysis) filters, where h is a low pass filter and g is a high pass filter. Let the dual filters ĥ and ĝ is the wavelet reconstruction (synthesis) filters. One stage of decomposition is followed by reconstruction [16].

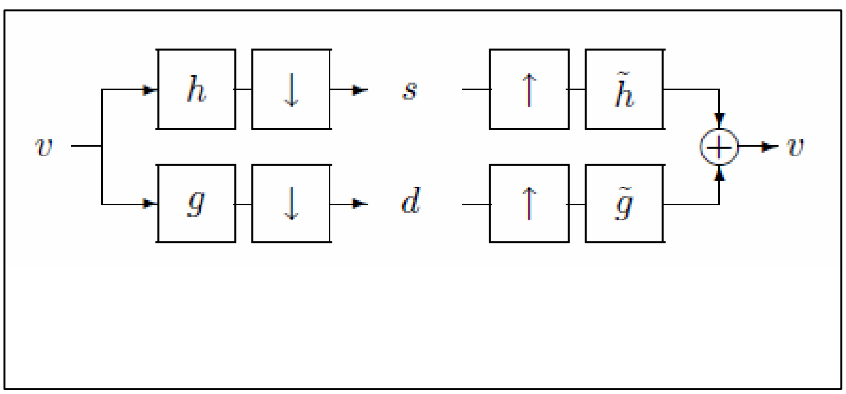



**Fig 4.1: Decomposition & Reconstruction of 1-D Signal using Filters**

The wavelet filters h, g, $\hat{h}$, $\hat{g}$ must satisfy the perfect reconstruction conditions,

$$h(z)\,\hat{h}(z) + g(z)\,\hat{g}(z) = 2$$
$$h(z)\,\hat{h}(-z) + g(z)\,\hat{g}(-z) = 0$$

Scaling the filters by some scale factors $\alpha, \beta$ and shifting by some even integers 2j, 2k preserves the perfect reconstruction conditions.

$$h'(z) = \alpha z^{2j} \; h(z)$$
$$\hat{h}'(z) = \alpha^{-1} z^{-2j}\,\hat{h}(z)$$
$$\hat{g}(z) = \beta z^{2k} \; g(z)$$
$$\hat{g}'(z) = \beta^{-1} z^{-2k}\,\hat{g}(z)$$

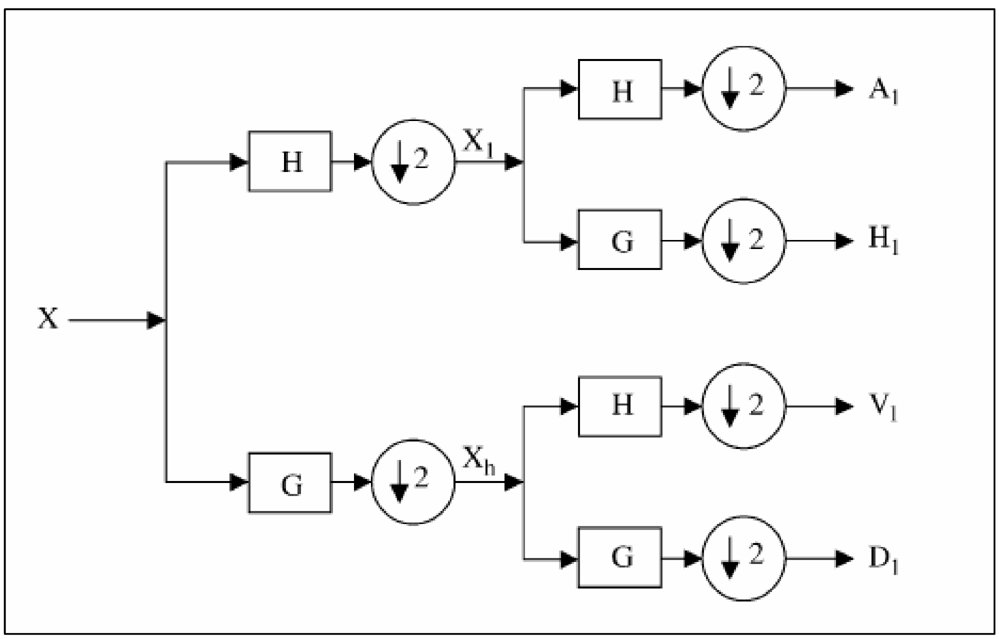



**Fig 4.2: 1st Level Decomposition of Image**

As image is a 2D signal so it needs 2D wavelet transforms to decompose it. After decomposition we get different sub- bands. These sub-band images contain coarse approximations of the face as well as horizontal, vertical and diagonal details of faces at various scales. It is shown in the figure 4.2

In Fig. 4.2, the tree representation of one level, two-dimensional wavelet decomposition is shown. In this figure, G denotes high-pass filtering and H denotes low-pass filtering. Here down-sampling is done by a factor of 2. In the final stage of the decomposition we have four N/2×N/2 resolution sub-band images: A1, the scaling component containing global low-pass information, and three wavelet components, H1, V1, D1, corresponding, respectively, to the horizontal, vertical and diagonal details [6].

In our experiment we are using five types of wavelets. These wavelets are haar, daubechies, coiflets, biorthogonal and reverse biorthogonal. The coefficients for these wavelets are following. Here LO_D ,HI_D , LO_R , HI_R are filter coefficient for low pass decomposition filter, high pass decomposition filter, low pass reconstruction filter and high pass reconstruction filter.

## Haar

LO_D = [0.7071 0.7071]
HI_D = [-0.7071 0.7071]
LO_R = [0.7071 0.7071]
HI_R = [0.7071 -0.7071]

## Daubechies4

LO_D = [-0.0106 0.0329 0.0308 -0.1870 -0.0280 0.6309 0.7148 0.2304]
HI_D = [-0.2304 0.7148 -0.6309 -0.0280 0.1870 0.0308 -0.0329 -0.0106]
LO_R = [0.2304 0.7148 0.6309 -0.0280 -0.1870 0.0308 0.0329 -0.0106]
HI_R = [-0.0106 -0.0329 0.0308 0.1870 -0.0280 -0.6309 0.7148 -0.2304]

## Coiflets2

LO_D = [-0.0007 -0.0018 0.0056 0.0237 -0.0594 -0.0765 0.4170 0.8127 0.3861 -0.0674 -0.0415 0.0164]
HI_D = [-0.0164 -0.0415 0.0674 0.3861 -0.8127 0.4170 0.0765 -0.0594 -0.0237 0.0056 0.0018 -0.0007]
LO_R = [0.0164 -0.0415 -0.0674 0.3861 0.8127 0.4170 -0.0765 -0.0594 0.0237 0.0056 -0.0018 -0.0007]
HI_R = [-0.0007 0.0018 0.0056 -0.0237 -0.0594 0.0765 0.4170 -0.8127 0.3861 0.0674 -0.0415 -0.0164]

## Biortogonal6.8

LO_D = [0 0.0019 -0.0019 -0.0170 0.0119 0.0497 -0.0773 -0.0941 0.4208 0.8259 0.4208 -0.0941 -0.0773 0.0497 0.0119 -0.0170 -0.0019 0.0019]
HI_D = [0 0 0 0.0144 -0.0145 -0.0787 0.0404 0.4178 -0.7589 0.4178 0.0404 -0.0787 -0.0145 0.0144 0 0 0 0]
LO_R = [0 0 0 0.0144 0.0145 -0.0787 -0.0404 0.4178 0.7589 0.4178 -0.0404 -0.0787 0.0145 0.0144 0 0 0 0]
HI_R = [0 -0.0019 -0.0019 0.0170 0.0119 -0.0497 -0.0773 0.0941 0.4208 -0.8259 0.4208 0.0941 -0.0773 -0.0497 0.0119 0.0170 -0.0019 -0.0019]

## Reverse Biorthogonal6.8

LO_D = [0 0 0 0 0.0144 0.0145 -0.0787 -0.0404 0.4178 0.7589 0.4178 -0.0404 -0.0787 0.0145 0.0144 0 0 0]
HI_D = [-0.0019 -0.0019 0.0170 0.0119 -0.0497 -0.0773 0.0941 0.4208 -0.8259 0.4208 0.0941 -0.0773 -0.0497 0.0119 0.0170 -0.0019 -0.0019 0]
LO_R = [0.0019 -0.0019 -0.0170 0.0119 0.0497 -0.0773 -0.0941 0.4208 0.8259 0.4208 -0.0941 -0.0773 0.0497 0.0119 -0.0170 -0.0019 0.0019 0]
HI_R = [0 0 0 0 0.0144 -0.0145 -0.0787 0.0404 0.4178 -0.7589 0.4178 0.040 -0.0787 -0.0145 0.0144 0 0 0]

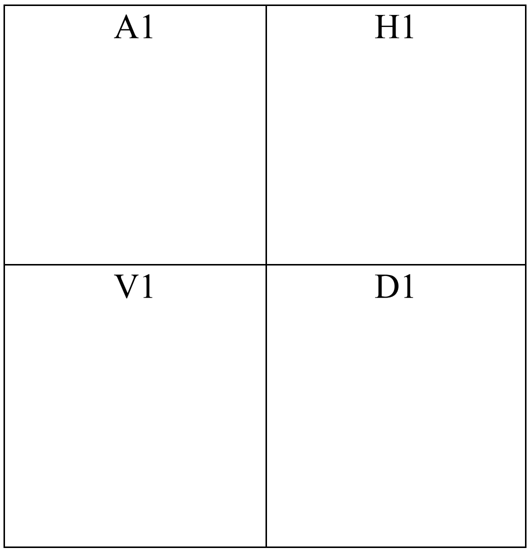
## 4.3 Feature Extraction and Experiment

In Fig. 4.3 and Fig 4.4 the schematics of the wavelet decomposition used in our work is shown. The letters in the Figures are used to differentiate the scaling component or the orientations of the wavelet components, while the accompanying numbers denote the level of decomposition.

In our experiment, we are using ORL face database. Each image of the database is resized to 128×128. For feature extraction first of all the sub-bands that are potentially insensitive to changes in expression are searched.

So in the first level, a 128×128 original face image is decomposed and four 64×64 pixels resolution sub-band images A1, H1, V1 and D1 are obtained. The H1, V1, and D1 components are not further decomposed, because we found their classification performance figures to be very low. Consequently we proceed to decompose only A1, yielding four 32×32 sub-band imagesA2, H2, V2 and D2. Same as the second in the third level, we decompose only A2 producing 4 16×16 sub-band images. In summary, we obtain 3 different sub-band images A1, A2 and A3 from the original face image and they are input for classification scheme.

In this way 128×128 face image corresponds to a point in 6376-dimensional huge feature space. On the other hand, face images are very similar, and therefore highly correlated. It follows than that they can be represented in a much lower dimensional feature subspace. PCA and ICA are the two popular methods to descend to such face subspaces. In our experiment we are using PCA.



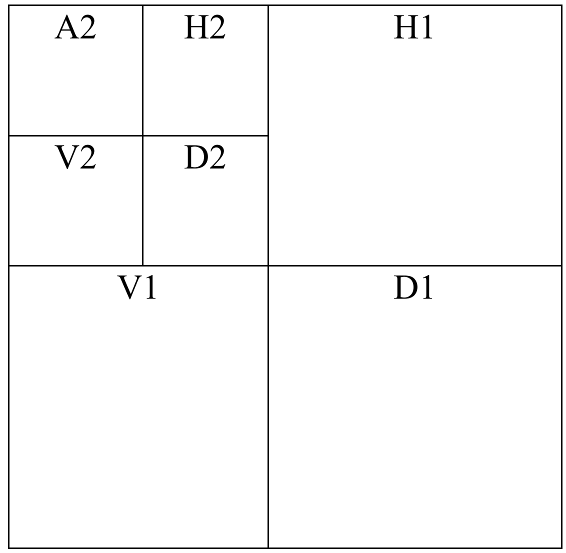




**Fig: 1st level Decomposition**

**Fig: 2nd level Decomposition**

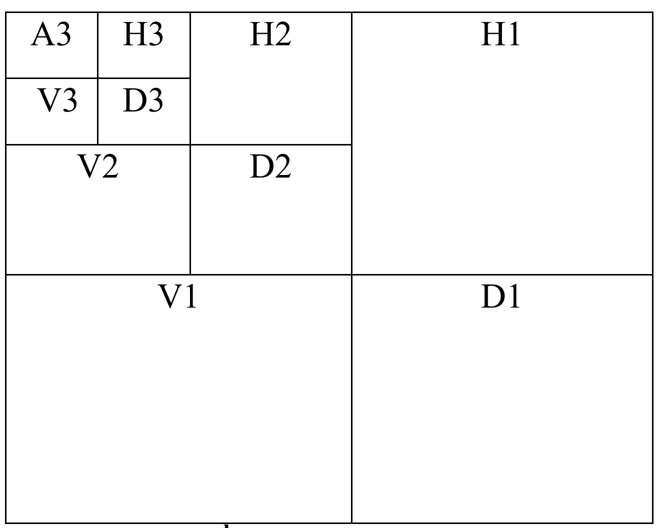



**Fig: 3rd level Decomposition**

**Fig 4.3: Different Levels of Decomposition in study**

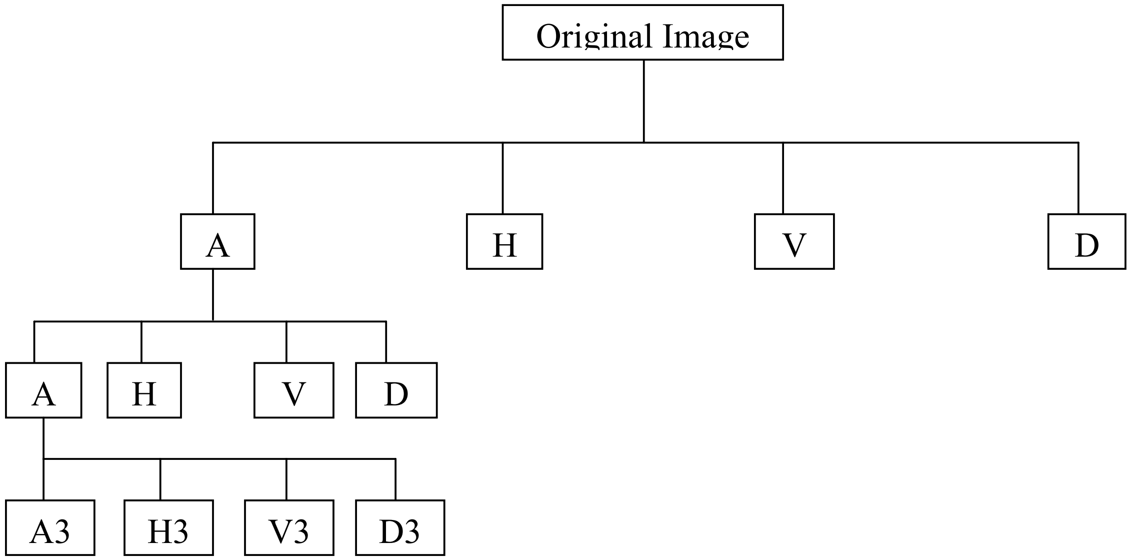



**Fig 4.4: Wavelet decomposition tree used in the study**

Principal component analysis (PCA) is based on the second-order statistics of the input image, which tries to attain an optimal representation that minimizes the reconstruction error in a least-squares sense. Eigen-vectors of the covariance matrix of the face images constitute the Eigen-faces. The dimensionality of the face feature space is reduced by selecting only the Eigen-vectors possessing largest Eigen-values. Once the new face space is constructed, when a test image arrives, it is projected onto this face space to yield the feature vector—the representation coefficients in the constructed face space. The classifier decides for the identity of the individual, according to a similarity score between the test image's feature vector and the PCA feature vectors of the individuals in the database.

The outcomes from the various wavelet channels are fused to achieve possibly higher correct recognition rates. We investigated three schemes, namely, fusing raw pixel values of the sub-bands, fusing PCA feature vectors extracted from the sub-bands, and fusing the classification decisions of the sub-bands. There can be different types of fusion technique. For example data fusion, feature fusion and decision fusion. We chose data fusion. The block diagram for it is shown below:

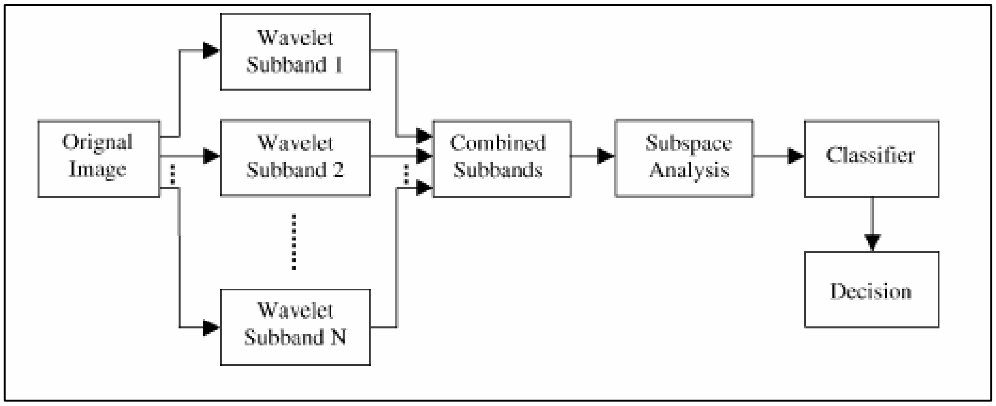



**Fig 4.5: Block diagram for Data Fusion**

In data fusion, lexicographically ordered pixels of the sub-band images are concatenated to construct a new data vector. Following this operation, the subspace projection and feature extraction are performed on the combined data vectors. The figure shows different sub-bands with Haar Wavelet.

**Fig 4.6: Different levels of Decomposition**

## 4.4 Experimental Results

In experiment we are varying the no. of training faces and testing faces along with the Wavelet type. The table below shows the overall success rate with different Wavelets.

**Table 4.1**

| No. of Training Faces | No of Testing Faces | Overall success rate | | | | |
|---|---|---|---|---|---|---|
| | | Wavelet used | | | | |
| | | Haar | Daubechies4 | Coiflets 2 | Biortogonal 6.8 | Reverse Biorthogonal 6.8 |
| 1 | 9 | 61.666 | 70.555 | 72.500 | 72.222 | 73.055 |
| 2 | 8 | 69.375 | 79.062 | 75.187 | 75.812 | 74.875 |
| 3 | 7 | 72.500 | 80.714 | 81.428 | 82.500 | 82.142 |
| 4 | 6 | 74.250 | 82.083 | 81.666 | 82.500 | 82.083 |
| 5 | 5 | 78.000 | 83.500 | 82.500 | 85.500 | 84.000 |
| 6 | 4 | 89.375 | 92.375 | 93.625 | 93.625 | 92.375 |
| 7 | 3 | 92.500 | 94.666 | 94.666 | 93.000 | 93.000 |
| 8 | 2 | 93.750 | 95.500 | 95.500 | 92.500 | 92.500 |
| 9 | 1 | 93.000 | 95.500 | 100.00 | 92.500 | 92.500 |

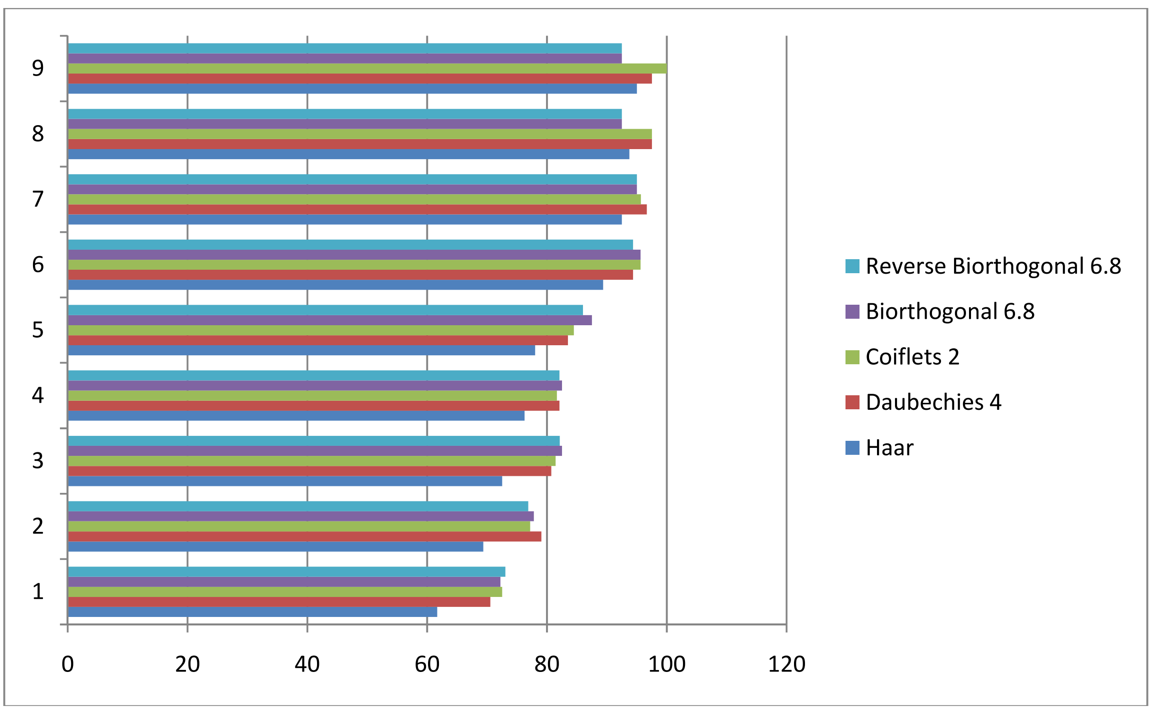



**Fig 4.7: Percentage Success of different types of Wavelets**

## 4.5 Conclusion

Wavelet is one of the most sounding methods of multi-resolution analysis of image processing purpose especially in face recognition, de-noising and compression. By getting different sub-bands, we can very easily select those sub-bands which represent the image in a better way. Due to this privilege, Wavelet based technique is working better than DCT based technique and PCA based technique even in large pose and illumination variations. This is clear from the results shown for ORL data base in Table 4.1.So Wavelet based Face Recognition system is appropriate for both type of situation. But it is generally used in large pose and illumination conditions.

# Chapter 5

# Conclusion & Suggested Future Work

## 5.1 Conclusion

From the above experiments the following points can be concluded:

1) If there are very less pose and illumination variations in the faces then DCT based recognition is a very good option as it is very simple to implement and has less computation complexity. But if there are large variations in pose or illumination then DCT based recognition is not a good option ,as in this case to represent the image we have to take large number of DCT coefficients, hence the system will be complex. Also in large pose and illumination condition DCT coefficients do not represent the face well. So results is not that much satisfactory.

2) In such conditions simple PCA or Wavelets with PCA is a good choice, as representation by any of them is very good. So, we are getting good recognition rate.

3) The factors which we should consider for face recognition based on Wavelet transform are computational cost and extracting important visual features. So a reasonable train of thought is that Wavelet transform is used to decompose face images at suitable levels, and then several approximation sub-bands and detail sub-bands can be fused effectively.

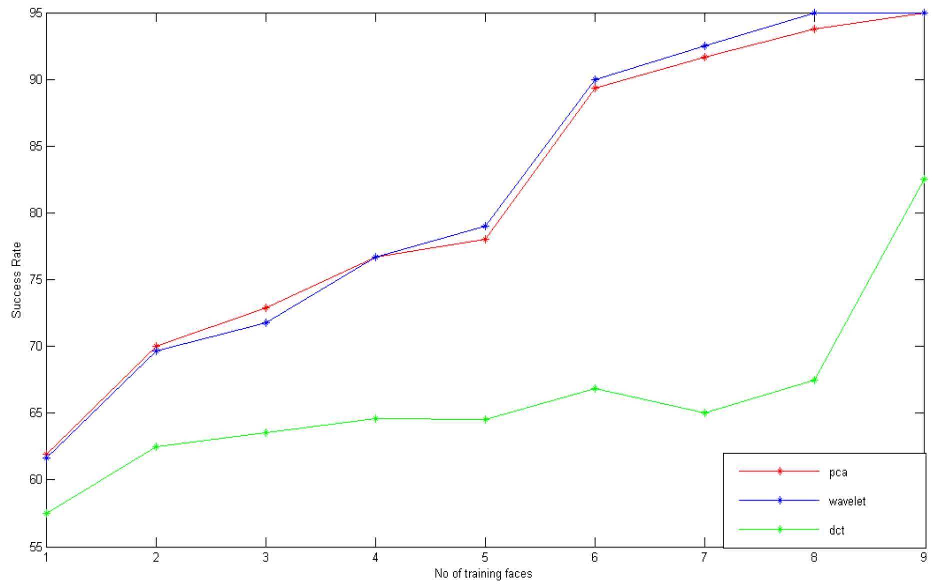



**Fig 5.1: Comparison of different algorithms for ORL database**

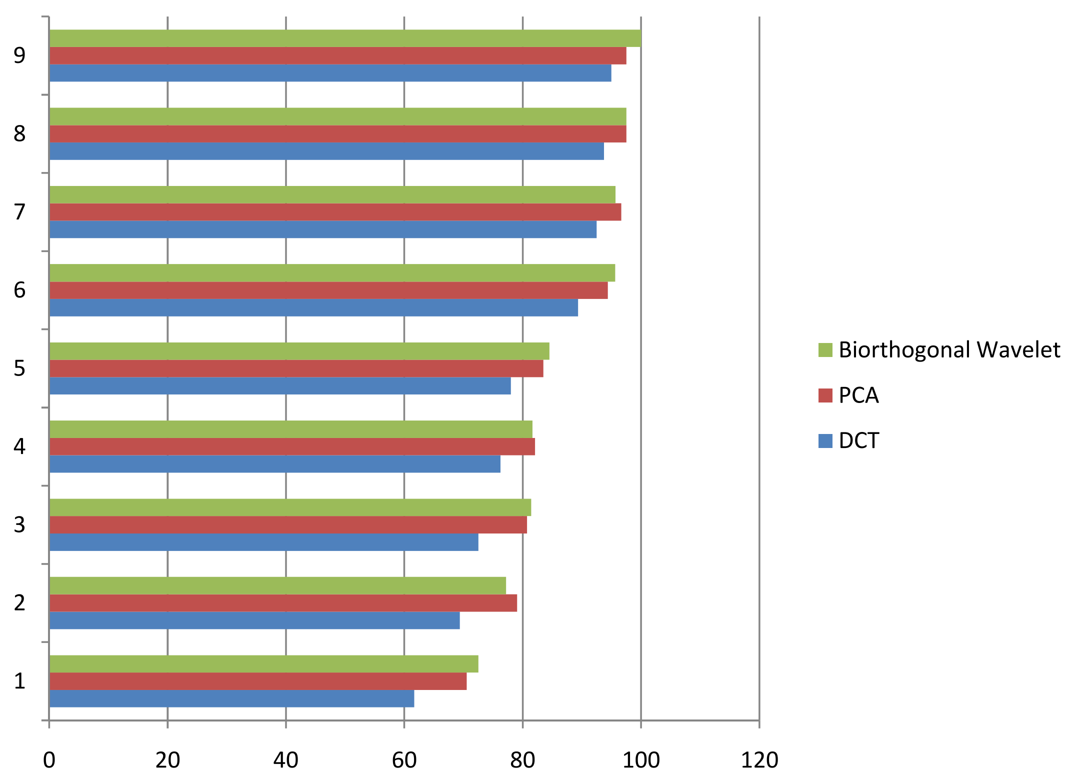



**Fig 5.2: Percentage Success of different algorithms for ORL database**

## 5.2 Suggested Future Work

From this work, in future anyone can proceed for some new approaches for face recognition. Some of the suggestions are as follows:

1) We can use LDA for better representation of feature vectors of faces.
2) For dimension reduction purpose IDA can be used.
3) For searching the best sub-band in wavelet based face recognition, we can use PSO and Genetic Algorithm.
4) For getting better result in pose and illumination variation conditions, Gabor wavelets can be used, also by using different fusion technique the recognition rate can be checked.
5) The RBF, SVM, SOM and fuzzy rule base can be used as classifier.
6) The GMM and HMM can be used to check the performance in a large face data base.

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