Face Recognition Using PCA and DCT Based Approach

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Certificate

This is to certify that the thesis titled, "Face Recognition Using PCA and DCT Based Approach" submitted by Tilak Acharya and Sunit Kumar Sahoo in partial fulfilment of the requirements for the award of Bachelor of Technology Degree in Electronics and Communication Engineering at National Institute of Technology, Rourkela (Deemed University) in an authentic work carried out by them under my supervision and guidance.

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Tilak Acharya Sunit Kumar Sahoo

Abstract

Face is a complex multidimensional structure and needs good computing techniques for recognition. Our approach treats face recognition as a two-dimensional recognition problem. In this thesis face recognition is done by Principal Component Analysis (PCA) and by Discrete Cosine Transform (DCT). Face images are projected onto a face space that encodes best variation among known face images. The face space is defined by eigenface which are eigenvectors of the set of faces. In the DCT approach we take transform the image into the frequency domain and extract the feature from it. For feature extraction we use two approach.. In the 1st approach we take the DCT of the whole image and extract the feature from it. In the 2nd approach we divide the image into sub-images and take DCT of each of them and then extract the feature vector from them.

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Chapter 1

Introduction

Chapter 1

Introduction

The information age is quickly revolutionizing the way transactions are completed. Human's day to day actions are increasingly being handled electronically, instead of face to face or with pencil and paper. This type of electronic transactions has resulted in a greater demand for fast and accurate user identification and authentication for establishing proper communication, access codes for buildings, banks accounts and computer systems for more secure transactions, PIN's for identification and security. By stealing other's ATM or any other smart cards, an unauthorized user can guess the correct personal information. Even after warnings, many people continue to choose easily guessed PIN's and passwords e.g. birthdays, phone numbers and social security numbers, horoscopes. present cases of identity theft have heightened the need for methods to prove that someone is truly who he/she claims to be.

Face recognition technology may solve this problem since a face is undeniably connected to its owner expect in the case of identical twins. It's non-transferable. The system can then compare scans to records stored in a central or local database or even on a smart card.

1.1 Biometrics

Biometrics is the technology for automated recognition or verification of the identity of a person using unique physical or behavioral characteristics such as fingerprints, hand geometry, iris, face, voice, and signatures. Biometrics is used in the process of authentication of a person by verifying or identifying that who he, she, or it claims to be, and vice versa. It uses the property that a human trait associated with a person itself like structure of finger, face details etc.

Biometrics may be classified into two categories.such as physiological and behavioural. Physiological biometrics (based on measurements and data derived from direct measurement of a part of the human body) include:

- Finger-scan
- Hand-scan
- Iris-scan
- Facial Recognition
- Retina-scan

Behavioral biometrics (based on measurements and data derived from an action) include:

- Voice-scan
- Signature-scan
- Keystroke-scan

A “biometric system” refers to the integrated hardware and software used to conduct biometric identification or verification.By comparing the existing data with the incoming data, we can verify the identity of a particular person which has more dynamic effects in the security and surveliance management, more convenient and easier in fraud detection, better than password or smart cards.

1.2 Face Recognition

Face is a complex multidimensional structure and needs good computing techniques for recognition. The face is our primary and first focus of attention in social life playing an important role in identity of individual. We can recognize a number of faces learned throughout our lifespan and identify that faces at a glance even after years. There may be variations in faces due to aging and distractions like beard, glasses or change of hairstyles.

Face recognition is an integral part of biometrics. In biometrics basic traits of human is matched to the existing data and depending on result of matching identification of a human being is traced. Face recognition technology analyze the structure, pattern, shape and positioning of the facial attributes. Eventhough face recognition is very complex technology it is largely software based. The analysis framework methodology establishes algorithms for each type of biometric device. Face recognition attempts to find a person in the image by taking a picture of the person and then facial features are extracted and implemented through algorithms which are eficient and some modifications are done to improve the existing algorithm models.

Computers that detect and recognize faces could be applied to a wide variety of practical applications including criminal identification, security systems, identity verification etc. Face detection and recognition is used in many places nowadays, in websites hosting images and social networking sites. Face recognition and detection can be achieved using technologies related to computer science. Features extracted from a face are processed and compared with similarly processed faces present in the database. If a face is recognized, it is known or

the system may show a similar face existing in database else it is unknown. In surveillance system if a unknown face appears more than one time then it is stored in database for further recognition. These steps are very useful in criminal identification. In general, face recognition mathematically models the problems in two different ways.in the first method it perform operation on whole image to get the desired result which is called principal component analysis. The other one take the image and process it in blocks which is called direct cosine transform analysis.

Chapter 2

Principal Component Analysis (PCA)

Chapter 2

2.1 Principal Component Analysis (PCA)

Principal component analysis (PCA) was invented in 1901 by Karl Pearson. It is a linear transformation based on statistical technique. It is used to decrease the dimension of the data or to reduce the correlation between them. It is a way of identifying patterns present in data, and expressing the data in such a way that their similarities and differences are highlight. Since patterns present in data can be hard to find in data of high dimension, where it can not be represented graphically, PCA is a powerful tool for face detection which is multi-dimensional.

The purpose of PCA is to reduce the large dimension of data space to a smaller intrinsic dimension of feature vector (independent variable), which are used to describe the data cost effectively. The first principal component is the linear combination of the original dimension along which the variance is maximum. The second principal component is the linear combination of the original dimension along which the variance is maximum and which is orthogonal to the first principal component. The n-th principal component is the linear combination with highest variance , subject to being orthogonal to n-1 principal component.

2.2 PCA THEORY

Principal component analysis in signal processing can be described as a transform of a given set of n input vectors each of length K formed in the n-dimensional vector $x = [x_1, x_2, \ldots, x_n]^T$ into a vector y according to

$$y = A(x - m_x)$$

Each row of x have K variables belonging to one input.

m_x represents the mean or expectation of all input variables defined as:

$$m_x = E\{x\} = \frac{1}{K}\sum_{k=1}^{K} x_k$$

The matrix A in the above equation is derived from the covariance matrix C_x . Rows of the matrix A are the eigen vector of the covariance matrix arrange according to the decreasing order of their eigen value.

The covariance matrix is given by:

$$C_x = E\{(x - m_x)(x - m_x)^T\} = \frac{1}{K}\sum_{k=1}^{K}(x_k {x_k}^T - m_k {m_k}^T)$$

As x is a n dimensional vector so C_x is a nXn vector where each element is given by:

$$\mathrm{Cx(i, j)} = \mathrm{E}\{(x_i - m_i)(x_j - m_j)\}$$

Rows of A are orthogonal to each other. We choose the number of rows to be present in A, which is less than or equal to n, and represent the dimension to which we want to reduce y.

2.3 PCA In Face Recognition

The images of the faces we have are in two dimension , let us say of size NXN.

Our aim here is to find the Principal components (also known as Eigen Faces) which can represent the faces present in the training set in a lower dimensional space.

For all our calculations we need the input data i.e. the faces is a linear form so we map the NXN image into a $1XN^2$ vector. Let every linear form of the image in our training set be represented by I_n. Let the total no. of faces in the training set be represented as M.

Steps For Computation of the Principal components:

- We compute the mean of all the faces vectors :

$$Mean = \frac{1}{M}\sum_{i=1}^{M} I_i$$

- Next we subtract the mean from the image vector I_i.

$$K_i = I_i - mean$$

- We compute the covariance matrix C:

$$C = \frac{1}{M}\sum_{i=1}^{M} K_i K_i^T = BB^T \text{ } (N^2XN^2 \text{ matrix})$$

  Where $B = [K_1 \ K_2 \ K_3 \ \ldots\ldots\ldots \ K_M]^T$ (N^2 X M matrix)

- Our next step is to compute the eigen vector of the matrix C or BB^T, let it be u_i.

But BB^T has a very large size and the computation of eigen vector for it is not practically possible.

So instead we find the eigen vector for the matrix B^TB, let v_i be the eigen vectors.

$$B^TBv_i = l_iv_i$$

Relationship between v_i and u_i

$B^TBv_i = l_iv_i$

=> $BB^TBv_i = l_iAv_i$

=> $CBv_i = l_iBv_i$

=>$Cu_i = l_iu_i$ where $u_i = Bv_i$

So BB^T and B^TB have same eigen value and there eigen vector are related by $u_i = Bv_i$

The M eigenvalues of B^TB (along with their corresponding eigenvectors) correspond to the M largest eigenvalues of BB^T (along with their corresponding eigenvectors).

- So now we have the M best eigen vector of C. From that we choose N1 best eigen vectors i.e. with largest eigen value.
- The N1 eigen vector that we have chosen are used as basis to represent the faces. The eigen vectors should be normalised. The eigen vectors are also referred to as eigen faces because when it is transformed into a N X N matrix it appears as "ghostly faces" consisting features of all the training faces.

Representing faces onto this basis:

Each face (minus the mean) K_i in the training set can be represented as a linear combination of N1 eigenvectors:

$$K_i' = \sum_{j=1}^{N1} w_j u_j \ , \qquad (w_j = u_j^T K_j)$$

w_j is the projection of K_j on to the eigen vector u_j

So each normalised face Ki can be represented in form of the vector,

$$W_i = [w_1^i \quad w_2^i \ldots\ldots \quad w_{N1}^i]^T$$

Recognising An Unknown Face:

Given an unknown face image (centred and of the same size like the training faces) we follow these steps to recognise it:

- We first convert it to the linear form , I
- Then we normalise it by subtracting the mean from it

  K = I –mean
- Next we project K on all the N1 eigen vectors to obtain the vector W

  $$W = [w_1 \;\; w_2 \;\; \ldots\ldots \;\; w_{N1}]^T$$

  where $w_i = {u_i}^T K$
- Now we find $e_r = \min_l \|W-W^l\|$

  Where $\left\||W - W^l|\right\| = \sum_{i=1}^{N1}(w_i - w_i^l)^2$
- So e_r gives the minimum distance the given face has from another face belonging to the training set. And the given face belongs to that person to whom the face in the training set belongs.
- If the value of e_r is greater than the threshold T_1 but less then threshold T_2 then we can say that it doesn't belong to any one in the given training set.

- If e_r is greater than threshold T_2 we can say that the given image doesn't belong to face space and hence is not the image of a face.

Chapter 3

Discrete Cosine Transform (DCT)

Chapter 3

Discrete Cosine Transform (DCT)

3.1 Introduction

A transform is a mathematical operation that when applied to a signal that is being processed converts it into a different domain and then can be again is converted back to the original domain by the use of inverse transform.

The transforms gives us a set of coefficients from which we can restore the original samples of the signal. Some mathematical transforms have the ability to generate decorrelated coefficients such that most of the signal energy is concentrating in a reduced number of coefficients.

The Discrete Cosine Transform (DCT) also attempts to decorrelate the image data as other transforms. After decorrelation each transform coefficient can be encoded independently without losing compression efficiency. It expresses a finite sequence of data points in terms of a sum of cosine functions oscillating at different frequencies. The DCT coefficients reflect different frequency component that are present in it. The first coefficient refers to the signal's lowest frequency(DC component) and usually carries the majority of the relevant information from the original signal. The coefficients present at the end refer to the signal's higher frequencies and these generally represent the finer detailed. The rest of the coefficients carry different information levels of the original signal.

3.2 Definition

Ahmed, Natarajan, and Rao (1974) first introduced the discrete cosine transform (DCT) in the early seventies. Ever since, the DCT has become very popular, and several versions have been proposed (Rao and Yip, 1990).

The DCT was categorized by Wang (1984) into four slightly different transformations named DCT-I, DCT-II, DCT-III, and DCT-IV.

Here we are using only DCT-II and is referred to as DCT and DCT-III as inverse DCT henceforth.

One dimensional DCT transform is defined as :

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

$0 \leq k \leq N-1$

Where u(n) in the input sequence of length N and its DCT is v(k) and

α (0) = $\sqrt{1/N}$

α (k) = $\sqrt{2/N}$ $\qquad 1 \leq k \leq N-1$

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

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

In 2 dimension the DCT is defined as :

$$C(u,v) = \alpha(u)\alpha(v)\sum_{x=0}^{N-1}\sum_{y=0}^{N-1} f(x,y)\cos[\frac{(2x+1)\pi u}{2N}]\cos[\frac{(2y+1)\pi v}{2N}]$$

for $u,v = 0,1,2,\ldots,N-1$ and $\alpha(u)$ and $\alpha(v)$ are defined above.

Its inverse is given by:

$$C(u,v) = \sum_{u=0}^{N-1}\sum_{v=0}^{N-1} \alpha(u)\alpha(v)C(u,v)\cos[\frac{(2x+1)\pi u}{2N}]\cos[\frac{(2y+1)\pi v}{2N}]$$

for $x,y = 0,1,2,\ldots,N-1$.

3.3 PCA IN DCT DOMAIN

In the pattern recognition letter by Weilong Chen, Meng Joo Er , Shiqian Wu it has been proved that we can apply the PCA directly on the coefficient of Discrete Cosine Transform. When PCA is applied on a orthogonally transformed version of the original data then the subspace projection obtained is same as compared to what is obtained by PCA on the original data. DCT and Block-DCT (it is the process of dividing the images into small blocks and then taking the DCT of each subimage) are also orthogonal transform, we can apply PCA on it without any reduction in the performance.

3.4 Basic Algorithm For Face Recognition

The basic Face Recognition Algorithm is discussed below. Both normalization and recognition are involved in it. The system receives as input an image containing a face .The normalized (and cropped) face is obtained and then it can be compared with other faces in the training set, under the same normalised condition conditions like nominal size, orientation and position. This comparison is done by comparing the 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.

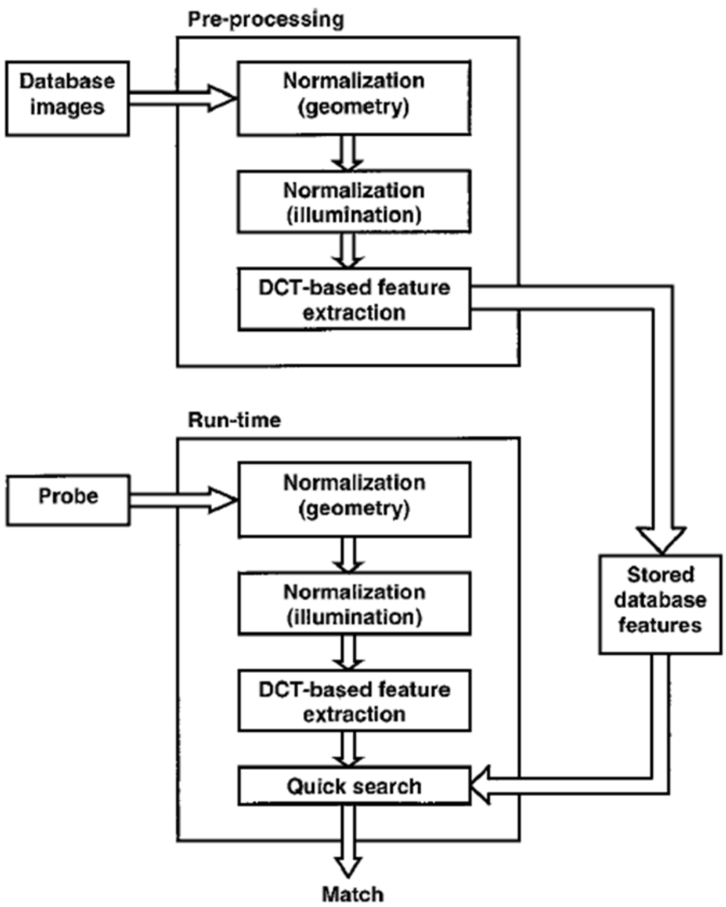


Fig:3.1 basic flow chart of DCT

This feature vector contains the mostly low and mid frequency DCT coefficients, as these are the ones that have maximum information contain and highest variance.

The feature vector which we obtain is still a very large in dimension. From the above discussion we know that PCA can be used in DCT domain without any change in the principal component. So we use the technique of PCA discussed in the previous section for reducing the dimensionality of the feature vector.

Once we have defined the face space with the help of Eigen vectors , then we can find the projection of the feature vectors in that space.

The projection of the input face and the projection of the faces in the data base are compared by finding out the Euclidean distance between them. A match is obtained by minimising the Euclidean distance.

Chapter 4

Implementation

Chapter 4

Implementation

4.1 PCA

Matlab 2011a is used for coding. The face images are cropped and converted to grey scale images as grey scale images are easier for applying computational techniques in image processing. The database used in this project is Indian face databases by IIT KGP.

Fig. 4.1 few of the images from the database

We have conducted five sets of experiments by considering 5 , 10 , 20 , 40 and 60 each time. For each person we have taken a few no photos with different orientations and expressions.

In each experiment we have used the algorithm discussed in the previous chapter and have found out the principal components. Then by taking certain no of principal components at a time we have formed the face space.

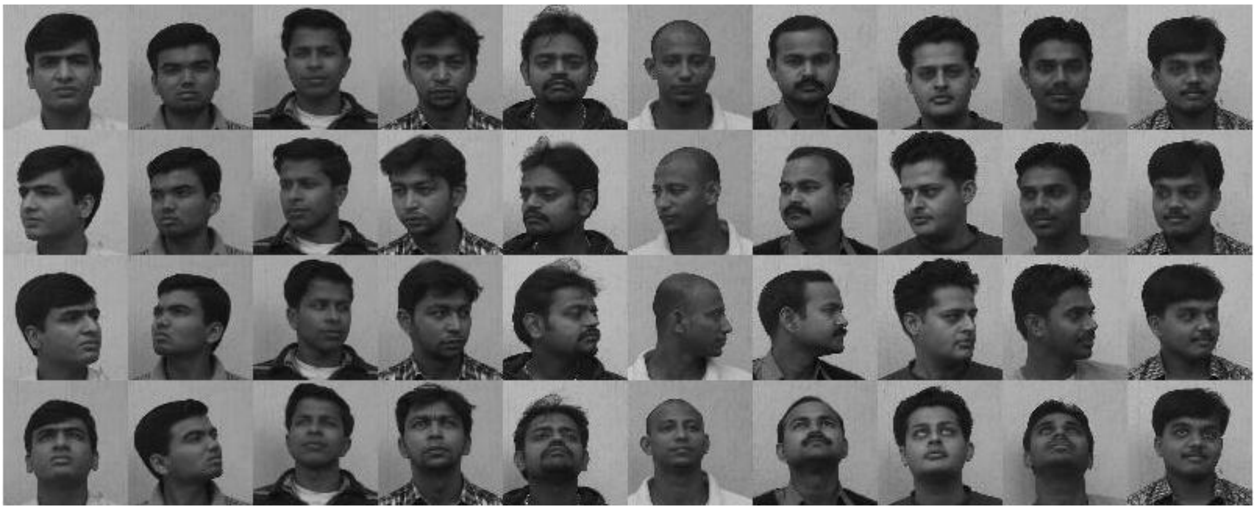


Fig. 4.2 Shows the image of 10 person in different pose

fig.4.3 mean of the above 40 faces

After the face space is formed we take a unknown face from the data base, normalize it by subtracting the mean from it .

Then we project it on the eigen vectors and derive its corresponding components.

Next we evaluate the Euclidian distance from the feature vector of other faces and find the face to which it has minimum distance. WE classify the unknown image to belong to that class (provided the minimum distance is less than the defined threshold).

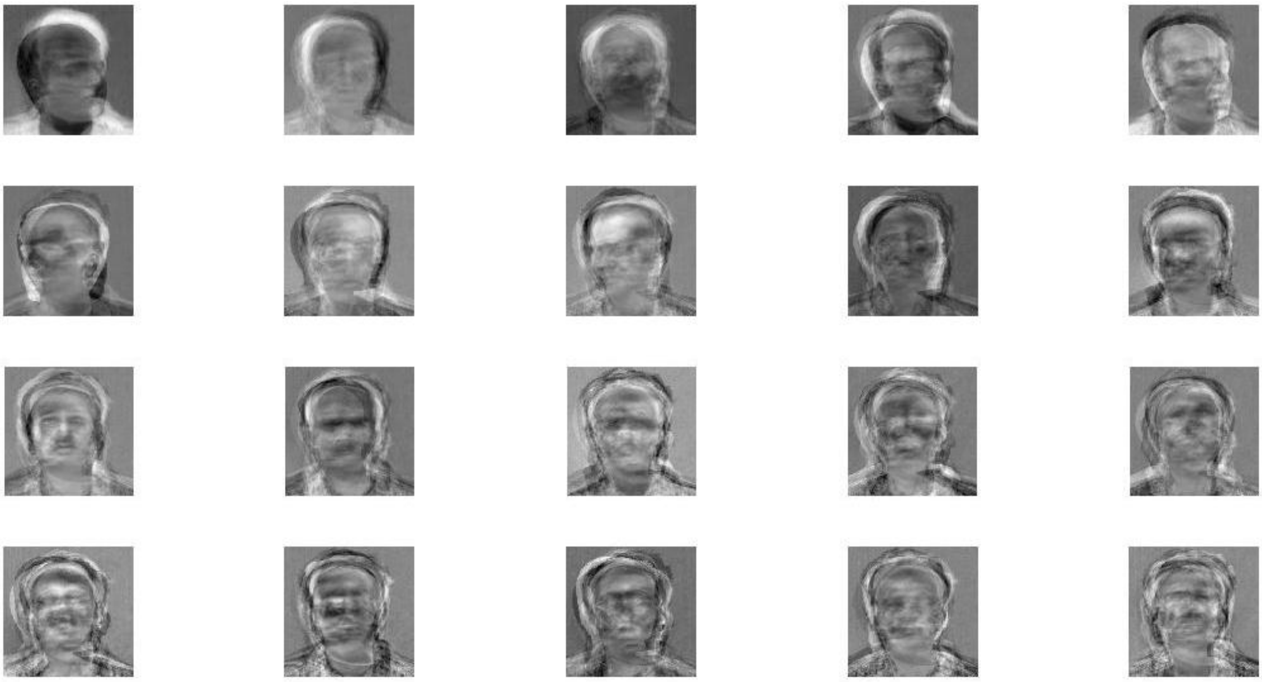


Fig 4.4 eigenfaces

4.2 DCT

We have used Matlab 2011a is used for implementation. We use the same data base as the above case. The face images are cropped and changed grey level. Next we convert the image to DCT domain for feature extraction. The feature vector is dimensionally much less as compared to the original image but contains the required information for recognition.

The DCT of the image has the same size as the original image. But the coefficients with large magnitude are mainly located in the upper left corner of the DCT matrix.

Low frequency coefficients are related to illumination variation and smooth regions (like forehead cheek etc.) of the face. High frequency coefficients represent noise and detailed information about the edijes in the image. The mid frequency region coefficients represent the general structure of the face in the image.

Hence we can't ignore all the low frequency components for achieving illumination invariance and also we can't truncate all the high frequency components for removing noise as they are responsible for edges and finer details.

Here we are going to consider two approach for feature extraction:

i. Holistic approach (we take the DCT of the whole image)

ii. Block wise approach (we divide the image into small sub-images and take their DCT)

In holistic approach we take the DCT of the whole image and extract the feature vector from it. In block wise approach we divide the image into many sub-images and then take DCT of each of them. We extract the feature vector from each of them and concatenate then to form the final feature vector.

HOLISTIC APPROACH

We take DCT of the image. Here our image size is 480 x 480. Next we convert the DCT of the image into a one dimensional vector by zigzag scanning. We do a zigzag scanning so that in the vector the components are arranged according to increasing value of frequency.

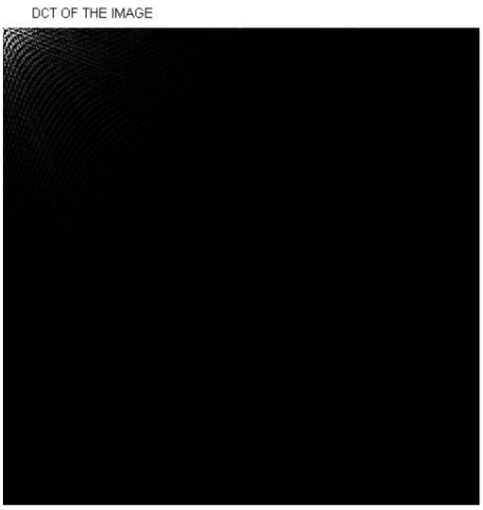


fig: 4.5sample image

fig:4.6 dct of the image

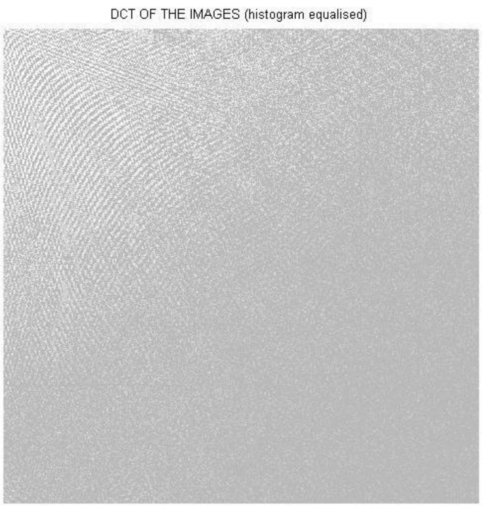


fig:4.7 histogram equalized version of the DCT

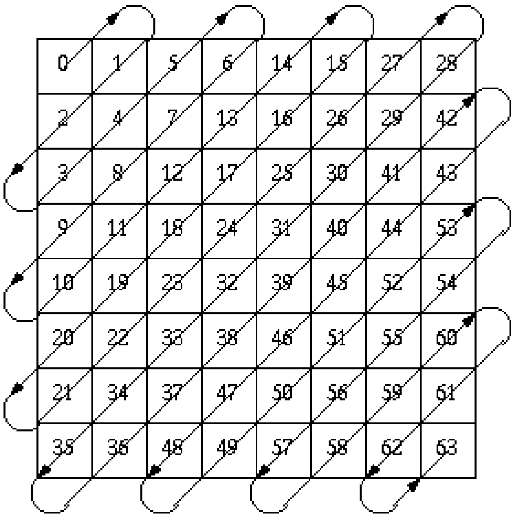


fig:4.8 show the manner in which zigzag scanning is done

From the plot of the vector we observe that the low- frequency components have high magnitude high frequency component have very less magnitude (i.e. much less than 1).

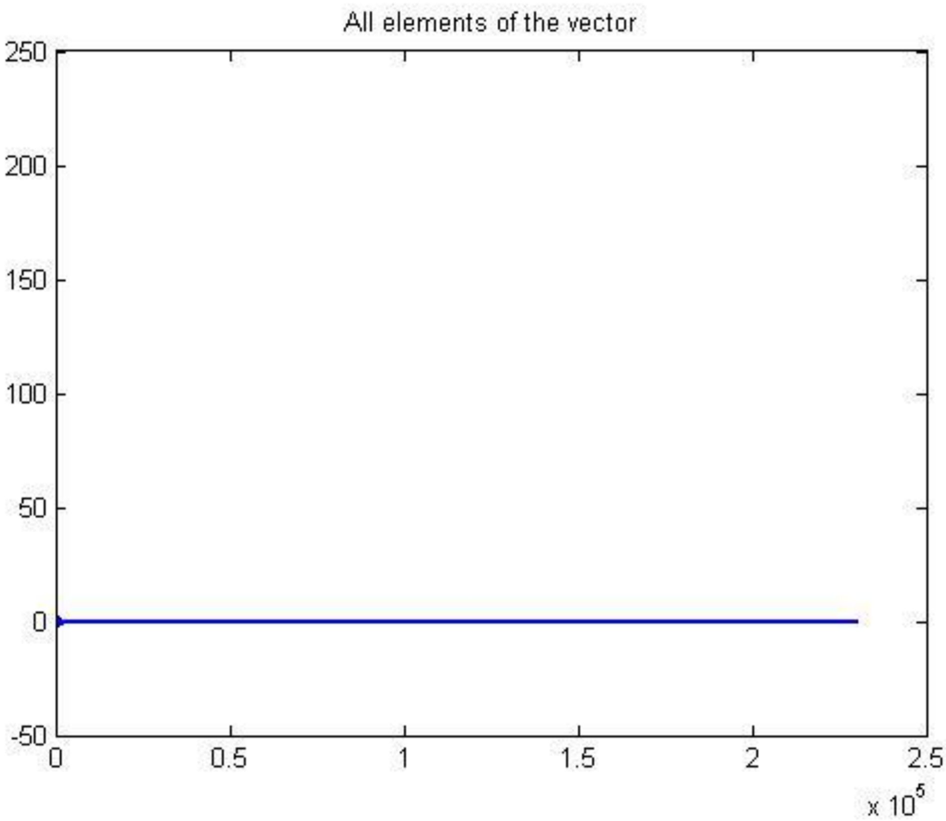


Fig: 4.9showing all the elements of the vector

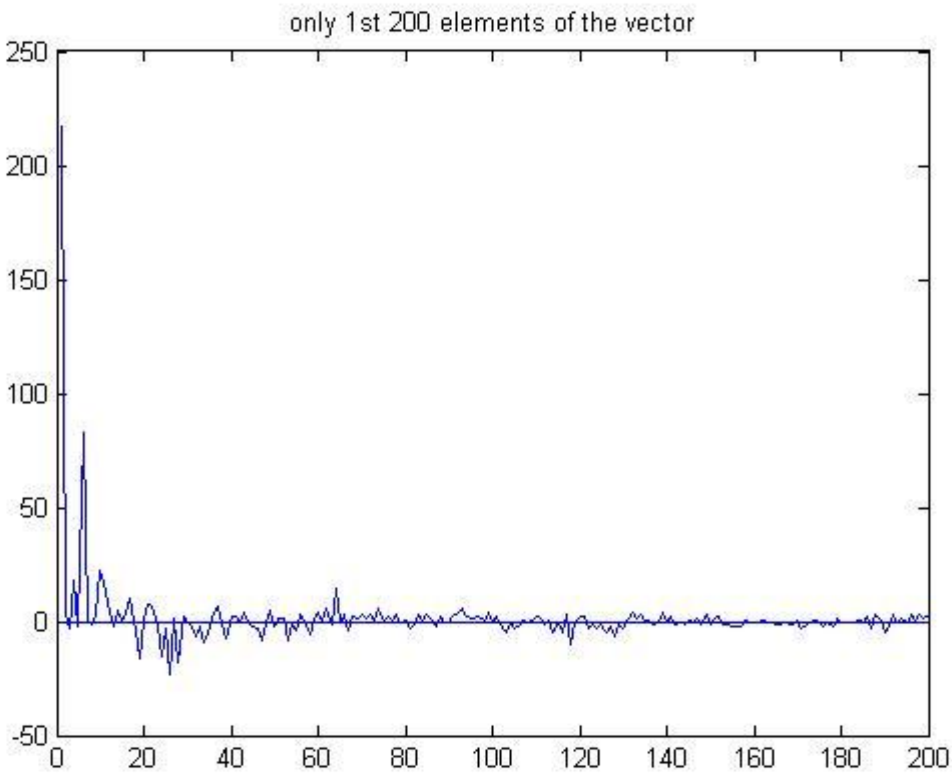


Fig : 4.10showing only the 1st 200 components

Now we divide the whole range of frequency into three equal sections and derive the coefficient of feature vector from each section.

In case of low frequency section we reject the 1st three terms and consider the next 800 terms. We reject the 1st three terms to achieve illumination invariance.

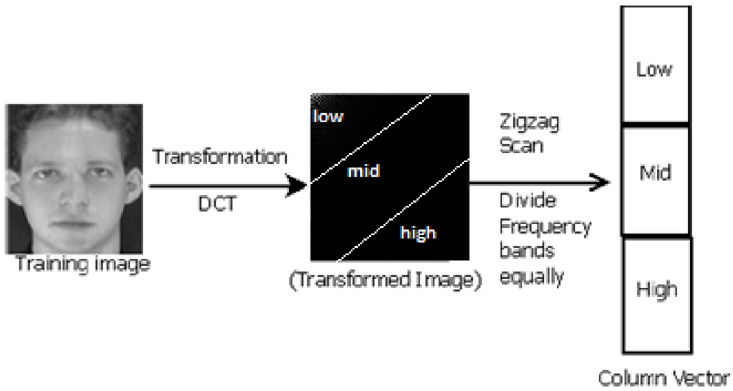


Fig: 4.11it shows the division of the whole range of frequency into three region.

In case of mid and high frequency section we find the position where the components with high value generally occur. We find this by comparing the images of the DCT of the images in the training set. Once the position whose values are to be considered are fixed then we obtain the coefficient from those position and include them in the feature vector. Here in our case we are considering 100 coefficient from each section.

So for each image we have obtained a feature vector of size 1000.

Next we apply PCA on these feature vector and find the corresponding eigen vector as discussed in the previous section.

We select the dimension according to our requirement and represent the feature vector in that space.

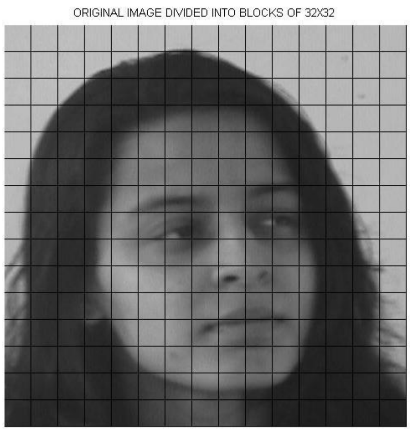
When we get a unknown face we first find its corresponding feature vector . Then we project the feature vector to the space described above. next we find the face to which it has minimum Euclidian distance and classify it accordingly.

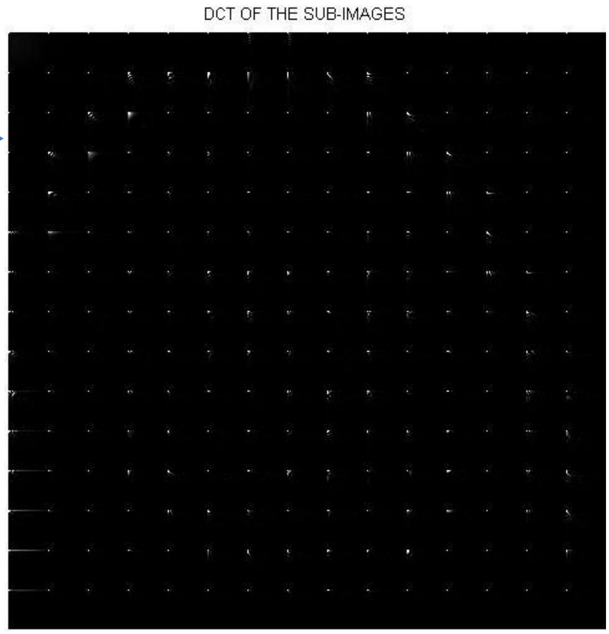
BLOCK DCT APPROACH

In this approach we divide the image into small blocks. Then we extract the feature vector from each block and combine them to get our required feature vector.We should choose the block size optimally. If it is too small then two adjacent blocks wouldn't be uncorrelated and it would give rise to redundant features. And if the block size is too high then we may miss out some feature.

Here we are considering block size of 32 x 32 pixels. So the original image is divided into 225 sub-images. Then we take the DCT of each sub image . So each DCT of sub-image contain 1024 coefficients.

From this we remove the DC component and then take the next 20 elements by scanning in a zigzag manner.





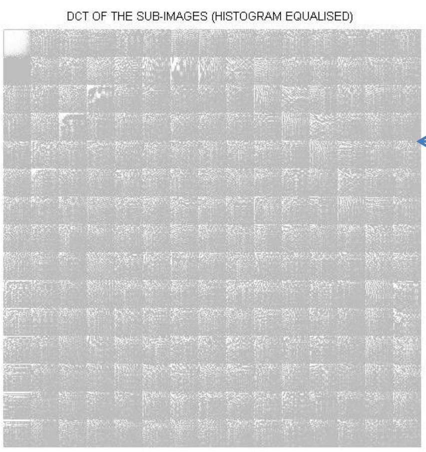


Fig:4.12 shows how a sample image is divided into sub images

DCT transform of the subimages and it histogram equalized version

Next we normalise the image we obtain from each sub-image and combine then to get our feature vector.

The feature vector obtained is still quite large, so we use PCA on the feature vector and obtain the eigen vector.

We select the dimension according to our requirement and represent the feature vector in that space.

When we get a unknown face we first find its corresponding feature vector . Then we project the feature vector to the space described above. next we find the face to which it has minimum Euclidian distance and classify it accordingly.

Chapter 5

Results

Chapter 5

Results

5.1 Result and Analysis

Threshold value of the test face image to Eigen face space which is Euclidean distance is taken as 7.6 which classifies the face as known or unknown. The values are compiled in a tabular form.

No. of Person	No. of Photos Per Person	Total no. of Test faces	Total no. of Eigenface Taken	Success Rate PCA Approach
5	4	20	5	71%
5	4	20	10	76%
5	4	20	15	84%
5	4	20	20	86%
10	4	40	5	69%
10	4	40	10	72%
10	4	40	15	82%
10	4	40	20	85%

Table 5.1: Comparison between different experimental Results of PCA approach

No. of Person	No. of Photos Per Person	Total no. of Test faces	Total no. of Eigenface Taken	Success Rate PCA Approach
20	8	160	10	67%
20	8	160	15	70%
20	8	160	20	75%
40	8	320	10	63%
40	8	320	15	69%
40	8	320	20	73%
60	8	480	10	55%
60	8	480	15	63%
60	8	480	20	70%

Table:5.2 Comparison between different experimental Results of PCA approach

No. of Person	No. of Photos Per Person	Total no. of Test faces	Total no. of Eigenface Taken	Success Rate DCT	Success Rate BLOCK-DCT
5	8	40	10	80%	82%
5	8	40	15	85%	85%
5	8	40	20	88%	90%
10	8	80	10	76%	78%
10	8	80	15	82%	83%
10	8	80	20	85%	86%
20	8	160	10	72%	74%
20	8	160	15	75%	76%
20	8	160	20	80%	80%

Table 5.3: Comparison between different experimental Results of DCT approach

Four different images for each mentioned condition were taken to test for five and ten different people. Light intensity is tried to keep low. Size variation of a test image is not altered to much extent. We can observe that normal expressions are recognized as face efficiently because facial features are not changed much in that case and in other cases where facial features are changed efficiency is reduced in recognition.similarly the results shows poor performances for lesser eigenfaces.

5.2 Average Success Rate

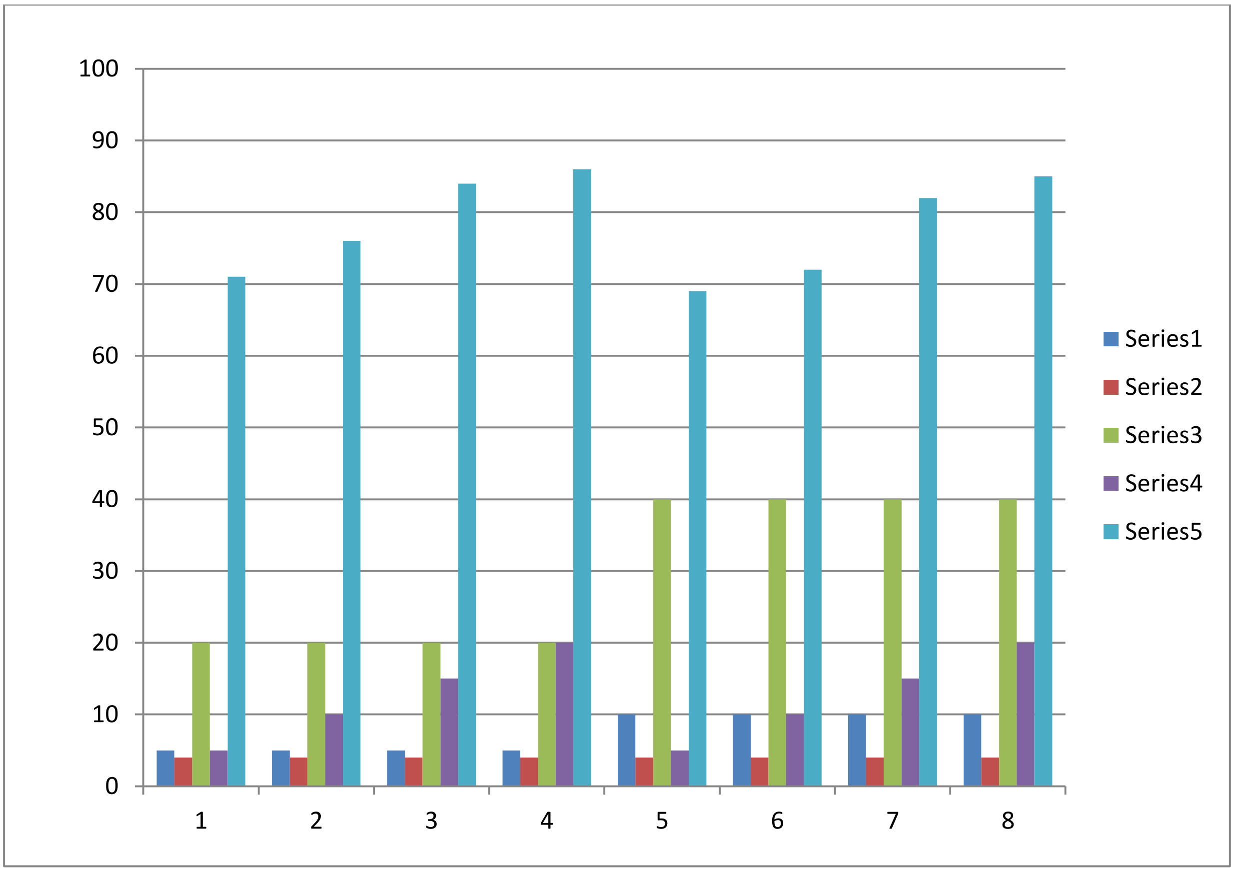
(71+ 76+ 84+ 86+ 69 + 72+82+85)/8 = 78.125% for PCA

(80+85+88+76+82+85+72+75+80)/9 = 80.333% for DCT

(82+85+90+78+83+86+74+76+80)/9 = 81.556% for Block-DCT

However, this efficiency cannot be generalized as it is performed on less number of test of images and conditions under which tested may be changed on other time.

5.3 Graph of the Result



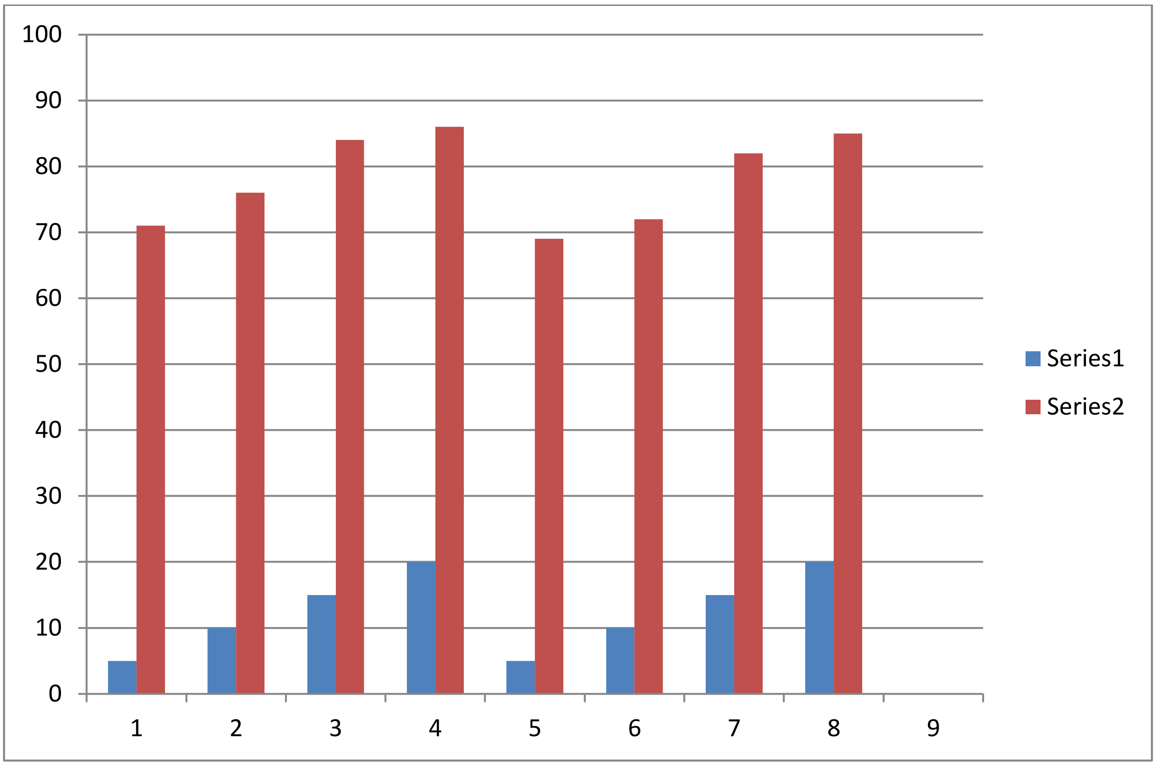
Series 1 : No. of Person

Series 2 No. of Photos Per Person

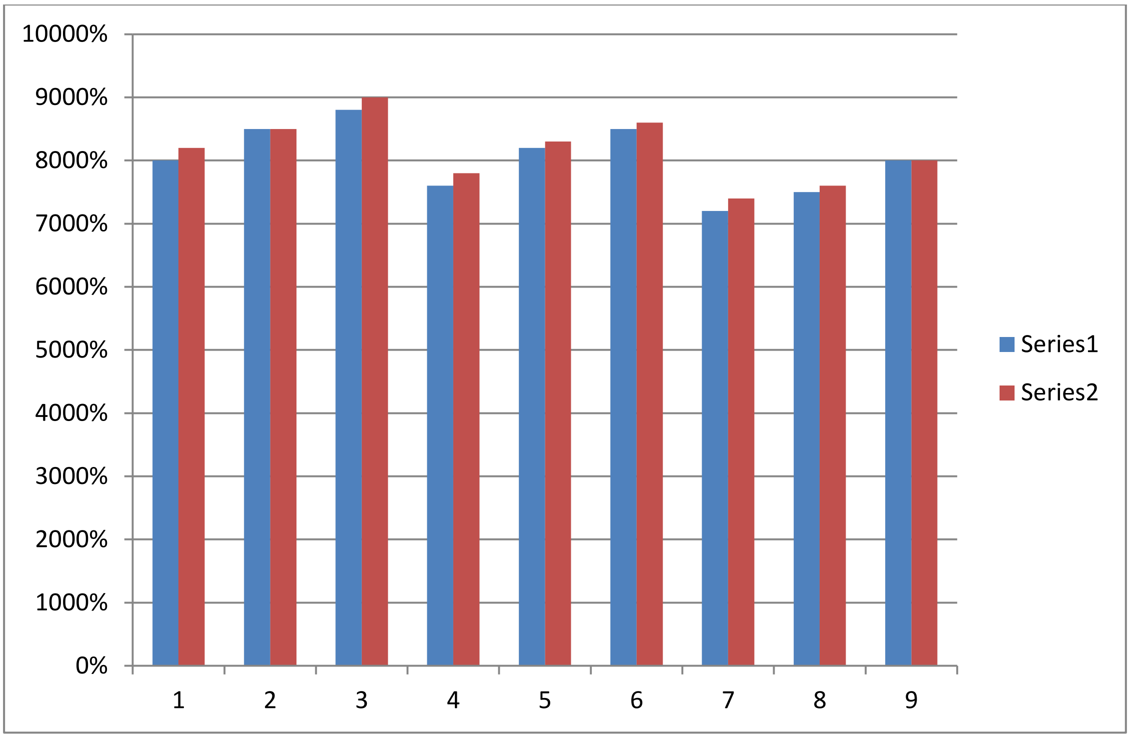
Series 3: Total no. of Test faces

Series 4: Total no. of Eigenface Taken

Series 5: Success Rate



series 1:Total no f faces   series 2: success rate in PCA



series 1:dct success rate   series 2: block dct success rate

Chapter 6

Conclusion

Chapter 6

Conclusion

In this thesis we implemented the face recognition system using Principal Component Analysis and DCT based approach. The system successfully recognized the human faces and worked better in different conditions of face orientation upto a tolerable limit. But in PCA, it suffers from Background (deemphasize the outside of the face, e.g., by multiplying the input image by a 2D Gaussian window centered on the face), Lighting conditions (performance degrades with light changes),Scale (performance decreases quickly with changes to the head size), Orientation (perfomance decreases but not as fast as with scale changes).

In block DCT based approach our the results are quite satisfactory.but it suffers from it's problem that all images should align themselves in the centre position minimizing the skewness of the image to lower level.

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