Feature Extraction of Face Using Various Techniques

Submitted By

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CERTIFICATE

This is to certify that thesis entitled **" Feature Extraction of Face Using Various Techniques "** has been completed by *Miss Shruti Biswal, Roll No. 110CS0121, National Institute of Technology, Rourkela, India* ,during the period July,2013-April, 2014 for the Final Year Project 2013-14 under the supervision of Prof. Ratnakar Dash.

(Prof. Ratnakar Dash)

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(Shruti Biswal)

DECLARATION

This thesis is a presentation of my original research work. Wherever contributions of others are involved, every effort is made to indicate this clearly, with due reference to the literature, and acknowledgement of collaborative research and discussions.

The work was done under the guidance of Professor Ratnakar Dash, at the National Institute Of Technology, Rourkela,Odisha.

Shruti Biswal

Abstract

This thesis aims at devising a novel method of feature extraction of face images which proves to be faster and more accurate than the existing methods defined by wavelet, curvelet and ridgelet transforms. DOST method of extracting features from face images keeps into account every minute detail of the face image i.e both spatial and frequency based features. The application of LDA method onto the DOST features in order to reduce the dimensionality of themethod further helps in making the process of feature extraction faster and hence reduces the time complexity of the feature extraction method. The matching is done by using different similarity measures such as euclidean distance. Results from different methods are evaluated and compared to present the effectiveness of this new method for feature extraction

Contents

Chapter 1

Introduction

1.1 Background and Motivation

Biometrics is the science of identifying, recognizing and verifying the credentials of an individual by making use of one or more of his biological traits. These traits include face, fingerprint, iris etc. Using face of a person has been the most common and visually prevalent method for recognition in biometrics. Facial feature extraction is an essential step in the face detection and facial expression recognition framework. In this research area, feature extraction is the most difficult and challenging task. Many researchers have proposed variety of techniques for feature extraction, and have tried to solve the problems that exist in this stage.Wavelet transform and ridgelet transform are the two main techniques that have been focussed on in this paper. The outline of this paper is as follows. In the next three sections, the theory and implementation about gabor filters,ridgelet transforms and curvelet transforms have deen discussed. In Chapter 2, the implementaion of DOST onto face images have been discussed which is a novel method for extracting face features. In Chapter 3, the application of LDA onto DOST features dimensionality reduction and classification has been explained.

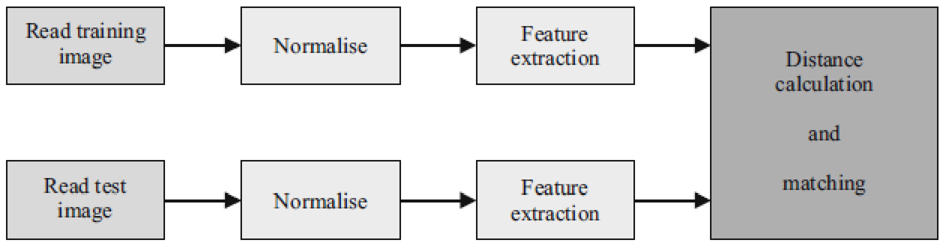

Figure 1.1: Block diagram of the recognition algorithm.

1.2 Gabor Transform

One of the most common and effective method to detect edges in an image is a wavelet transform. It has been widely used in feature extraction, especially in pattern recognition research area. Haar wavelet and Gabor wavelet have been used actively in face detection and proposed Haar-like-features that have a similarity with Haar wavelet in their face detection system and then the system was successful to detect face in simulation and real-time application. Gabor wavelet is favored among many researchers because of its outstanding performance in the task of facial expression analysis. Generally, Gabor filter bank which consists of filters with 5 frequencies and 8 orientations are used in many facial expression recognition systems. However, it has a limitation which is the processing time of Gabor feature extraction is very long and its dimension is prohibitively large [1][2]. In some previous proposed feature extraction used all 40 filters of Gabor filters while some of them used a few selected frequencies and orientations to reduce the processing time [3]. In this paper, edge-based facial feature extraction is proposed. This work is focusing on the extraction of specific facial components which are eyes, eyebrows, nose and mouth. Besides, the details or skin texture on face image like wrinkles are also extracted. In this study, Gabor wavelet and convolution filters are used as edge detectors. We select specific frequency andorientation for Gabor wavelet and specific convolution kernels for convolution filters to extract the facial features. Each edge detector extracts specific part of facial features on face image. The output images of the edge detection are added together, so that the final output presents a complete face.

1.2.1 Overall Outlook of the System

The system that has been designed in this paper for facial face recognition has been shown in the following figure. The system consists of three modules:

a) Facial feature extraction using Gabor filter

b) Dimensionality reduction using Sparse Random Projection.

c) Finally, the obtained feature vectors are then classified using Euclidean Distance for difference calculation with an allowed threshold of 0.001

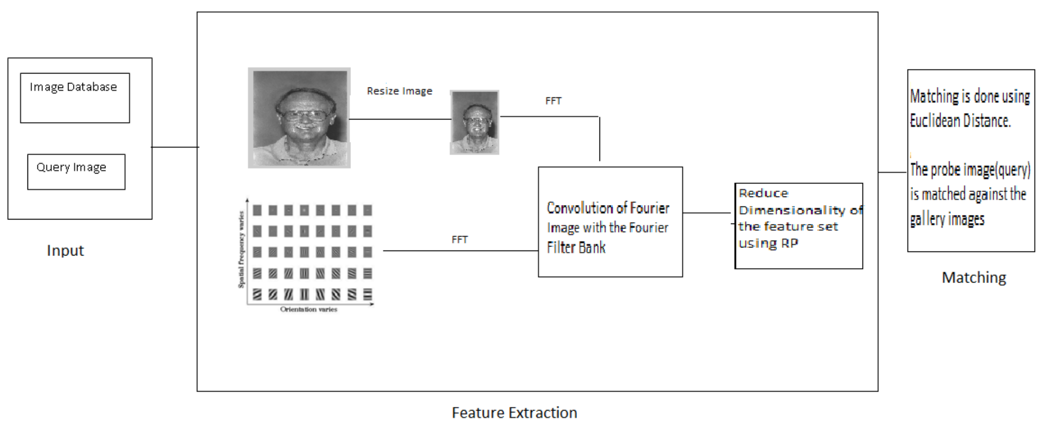

Figure 1.2: System Architecture for Facial Feature Extraction Using Gabor Filters

1.2.2 Extraction of Feature Sets

It has been seen from previous works that Gabor filters representation and extraction of face images is robust. However, the increased dimensionality of the Gabor features obtained have caused the method to be computationally very expensive. Therefore, there is a need to resize the original image using bilinear interpolation and then a method to reduce the size of the feature set.

Bilinear Interpolation

The original image was reduced gray scale in order to decrease the range of pixel values assumed and the size is reduced to 64×64 by bilinear interpolation. This is necessary to reduce the computation time. The resulting image is as shown in this figure and then the Fourier transformed is applied to the image.

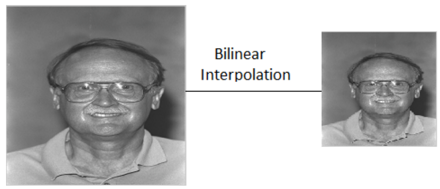

Figure 1.3: Bilinear Interpolation:Original image is scaled to a smaller size image

Fourier Transformed Image

Fourier Transformed image is the image I in the frequency domain as in this field every point represents a particular frequency contained in the image space of square image of size $N \times N$.The equation for transformation of the image

$$Fourier(m,n,I) = \frac{1}{N^2} \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} I(x,y) e^{-i2\pi \frac{mx+ny}{N}} \tag{1.1}$$

where, $m = 0, 1, ..., N-1$, $n = 0, 1, ..., N-1$ into its fourier transform is given as:

Gabor Filter

Gabor is a function that satisfies certain mathematical requirements extraction information is based on the use of a bank of Gabor filters, 8 orientations and 5 resolutions[4]. The 2D Gabor filter is defined by the follwing equation:

$$Gabor(x,y,u,v) = \theta(x,y,u,v)(\alpha - \beta) \tag{1.2}$$

where,

$\theta(x,y,u,v) = \frac{\|k_{\mu\nu}\|^2}{\sigma^2} exp(\frac{-\|k_{\mu\nu}\|^2(x^2+y^2)}{2\sigma^2})$

$\alpha = exp(ik_{\mu\nu} * (x,y))$

$\beta = exp(\frac{-\sigma^2}{2})$

Here (x,y) represents a 2-dimensional input point. The parameters μ and ν define the orientation and scale of the Gabor kernel. $\|\dot{}\|$ indicates the norm operator, and σ refers to the standard deviation of the Gaussian window in the kernel. The wave vector $K_{\mu\nu}$ is defined as:

$$k_{\mu\nu} = K_{\nu} \tag{1.3}$$

If 8 different orientations are chosen.Kmax is the maximum frequency, and f_{ν} is the spatial frequency between kernels in the frequency domain. In our configuration, 5 different scales and 8 orientations of Gabor wavelets are used, e.g.$\nu \in \{0, ..., 4\}$ and $\mu \in \{0, ..., 7\}$.Gabor wavelets are chosen with the parameters $Kmax, f, \sigma$:

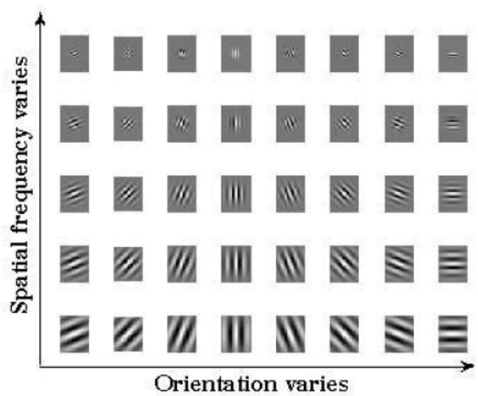

Figure 1.4: Gabor Filters of size 16×6 with 8 orientations and 5 resolutions

Algorithm 1 :Gabor Filter

1: Prepare 5×8 matrix Gabor each of size 16×16 as shown
2: Apply the Fourier transform to each matrix Gabor.
3: Apply Fourier to each image in the training set of size 32×32.
4: Convolution of the Fourier transform of the image size 32×32 by each image of the Fourier transformed Gabor size 16×16 having 8 orientations and 5 scales .
5: Construct the image $Fourier_{GaborIMG} 5 \times 8 \times 32 \times 32$ from the sub images

The use of Gabor filters is very expensive in computing time, due to the convolution of the whole image with filter size 16×16 . For this reason, we limit the use of the image size of 32×32 convolved with 40 Gabor filters: 8 orientations and 5 scales, then we resize the image result $FourierGaborIMG$ to 100×100,and Finally we reduce the vector of features by applying the method of random projection.

Sparse Random Projection

In the computer vision literature, many schemes have been investigated for finding projections that better represent data in lower-dimensional spaces. One benefit of feature extraction, which carries over to the proposed sparse representation framework, is reduced data dimension and computational cost. The choice of feature transformation is considered critical to the success of the algorithm.
Random Projection has been applied on various types of problems like machine learning. Its power comes from the strong theoretical results that guarantee a very high chance of success .

Matching

Probe images are fed into the system inorder to find the image of the subject against which it matches.for the matching purpose, the Euclidean distance is calculated between the probe image feature file and all the feature files of the gallery image. The case for which the difference lies below the threshold value can be considered as the matching subject and hence the recognition takes place.

1.3 Ridgelet Transform

To overcome the weakness of wavelets in higher dimensions, Candes and Donoho [5] [6] recently pioneered a new system of representations named ridgelets which deal effectively with line singularities in 2-D. The idea is to map a line singularity into a point singularity using the Radon transform. Then, the wavelet transform can be used to effectively handle the point singularity in the Radon domain. For practical applications, the development of discrete versions of the ridgelet transform that lead to algorithmic implementations is a challenging problem. Due to the radial nature of ridgelets, straightforward implementations based on discretization of continuous formulae would require interpolation in polar coordinates, and thus result in transforms that would be either redundant or can not be perfectly reconstructed.Previously the redundant approach is taken in defining discrete Radon transforms that can lead to invertible discrete ridgelet transforms with some appealing properties. For example, a recent preprint proposes a new notion of Radon transform for data in a rectangular coordinate such that the lines exhibit geometrical faithfulness. Their transform is invertible with a factor four over- sampled. However, the inverse transform is ill-conditioned in the presence of noise and requires an iterative approximation algorithm. In this paper, we propose a discrete ridgelet transform that achieves both invertibility and non-redundancy. In fact, our construction leads to a large family of orthonormal and directional bases for digital images, including adaptive schemes. As a result, the inverse transform is numerically stable and uses the same algorithm as the forward transform. Because a basic building block in our construction is the finite Radon transform , which has a wrap-around effect, our ridgelet transform is not geo metrically faithful. The properties of the new transform are demonstrated and studied in several applications.

1.3.1 Normalization

Normalization is the first and foremost step that needs to be carried out before any feature extraction method is applied[5]. In normalization, the image is transformed into a standard form which is devoid of any geometric or photometric distortions. Here, the normalization procedure is applied to all gallery and probe images before the actual recognition takes place. This begins with extraction of the facial image using the YCbCr colour space associated with the image. Y is the luminance component, while Cb and Cr are blue and red component of the image pixel respectively. The method uses the Cr component to extract the region of the image likely to correspond to skin. The largest such region is assumed to be the face and is used to crop the image.

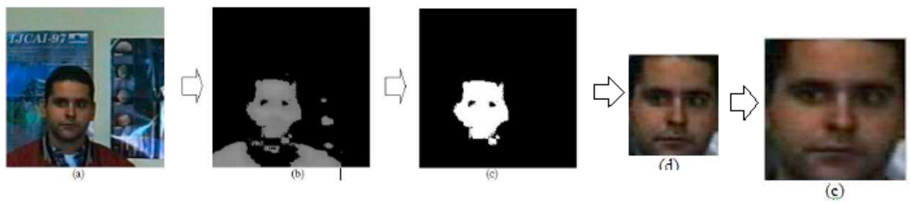

Figure 1.5: Normalization procedure: (a) Raw input image; (b) result of thresholding the Cr component; (c) largest area; (d) cropped face; (e) resized image;

Algorithm 2 :Normalization

1: Convert the RGB image into YCbCr colour space.
2: Segment the image, assuming that pixels having value of Cr greater than a fixed threshold are skin pixels.
3: Convert the image into binary image, where skin pixels are foreground and non-skin pixels become background. This operation generates a number of foreground areas, of which the largest area is assumed to be the face.
4: The foreground areas that are not part of the face are reclassified to background.
5: A bounding box is created about the face part and is cropped from the rest of the image.
6: The cropped image is rescaled to match the dimensions of the other faces in the database, ready for use in training and testing.

Although this method is rather simplistic, it does allow for a more rapid normalization than most existing approaches and can be improved further by incorporating eye-nose detection into the cropping phase.

1.3.2 Ridgelet Filters

In many image processing tasks, a sparse representation of an image is used in order to compact the image into a small number of samples. Wavelets are a good example for representing sparse geometrical image.[5][6] But regardless of advantages of the wavelets, they exhibit strong limitations when it comes to efficiency when applied in more than one dimension. Wavelets show good performance for piecewise smooth functions in one dimension, but fail to efficiently represent objects that have elements as lines or curvilinear structures (e.g. edges). The reason is that wavelets are non-geometrical and do not exploit the regularity of the edge curve. Wavelets are therefore good at representing zero-dimensional or point singularities. However, two-dimensional piecewise smooth signals (such as face images) have one-dimensional singularities meaning that wavelets will not accurately represent the smoothness of the image along the curve. The ridgelet transform is defined as the application of a 1D wavelet transform to the slices of the Radon transform where the angular variable θ is constant and t is varying. To complete the ridgelet transform, a one-dimensional wavelet transform must be taken along the radial variable in Radon space. The steps involved can be summarized as in the Figure 2.5.

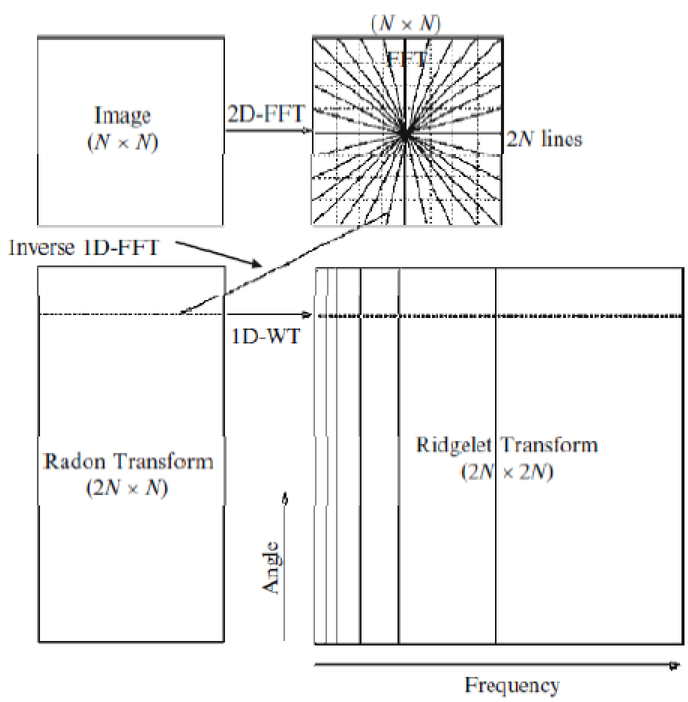

Figure 1.6: Schematic diagram for conversion of the image into its ridgelet transform

1.3.3 Proposed Algorithm

The proposed algorithm consists of a process of normalization followed by feature extraction and then recognition. The features are constructed from the LL1 (part of ridgelet image decomposition, as most energy can be found there. Recognition is then performed by calculating the Euclidean distance between feature vectors obtained from the LL1 part of the decomposed image. For the experiments, the feature vectors were typically several thousand elements wide.[6]

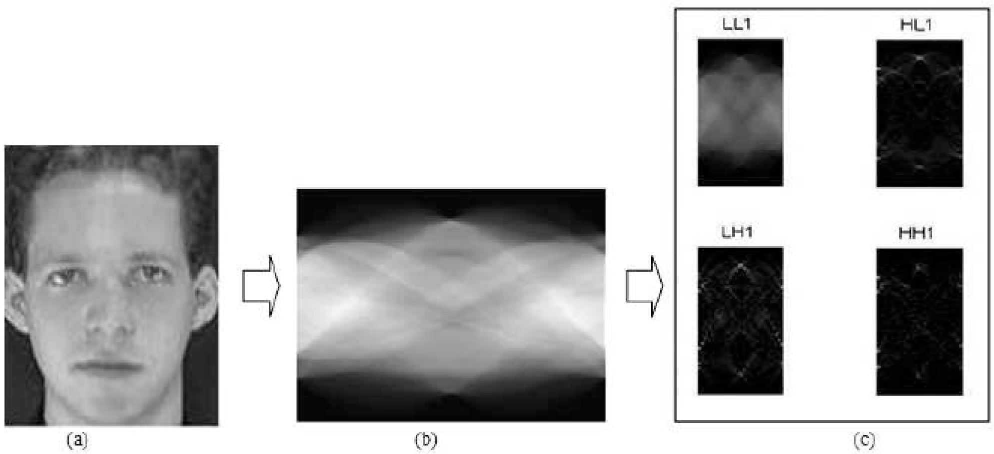

Figure 1.7: Example result of applying a ridgelet transform. (a) Original image; (b) Radon transform of image (Radon projections interval = 3 degrees); (c)Components of the ridgelet image decomposition.

Algorithm 3 :Ridgelet Transform

1: Normalize all the training images to extract the facial part of each input image
2: Apply the ridgelet transform to each of the normalized images.
3: Reshape the LL1 part of the decomposed images into feature vectors.
4: Acquire and normalize the test image.
5: Calculate the ridgelet transform of the test image.
6: Reshape the LL1 part of the decomposed test image to obtain the test image feature vector.
7: Calculate the Euclidean distance between the test image feature vector and each of the training image feature vectors.
8: The training image with the minimum Euclidean distance to the test feature vector is the correct face. (For verification applications, the Euclidean distance must be below a set threshold)

1.4 Curvelet Transform

Motivated by the need of image analysis, Candes and Donoho developed curvelet transform in 2000. Curvelet transform provides a highly redundant dictionary that represents the sparse representation of signals that have edges along the curve chosen to represent the face image. These are effective indetermining image activity at the curves. Initially, the curvelet transform was designed to be continuous.But for theprupose ofapplication to the arrays and images, Fast discrete CurvletTransformis used. 2D-FDCT is used on images to get the features extracted via Curvelet Transform.

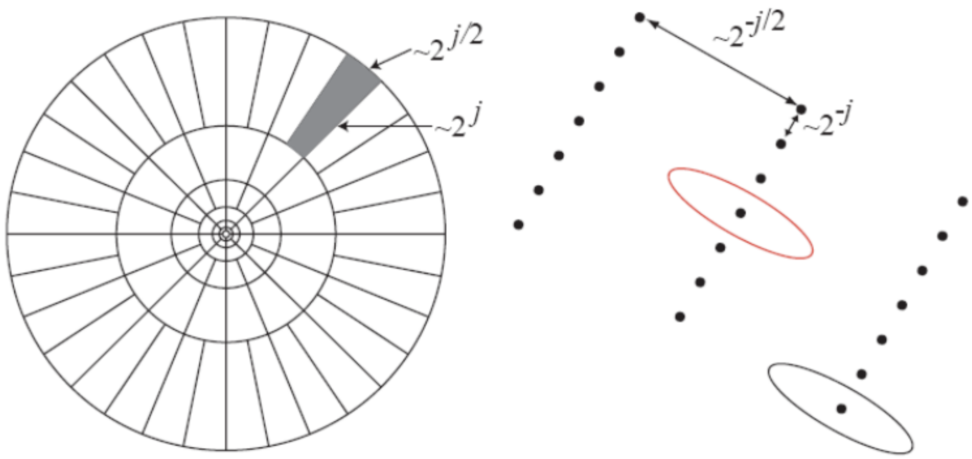

Figure 1.8: Curvelets in Fourier frequency (left) and spatial domain (right)[Candes et al. 2006]

Algorithm 4 :Curvelet Coefficient Calculation

1: Calculate 2D Fast Fourier Transform of the image
2: Divide 2D Frequency plane into wedges. The typical shape of wedges contribute to the division of the Fourier plane in angular and radial divisions.
3: Calculate Inverse Fourier Transform on each wedges to get the curvelet coefficient for that scale and angle

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1.4.1 Discrete Curvelet Transform Using Unequally Spaced Fast Fourier Transform

There are two different methods to implement 2D-FDCT:Curvelets via USFFT and Curvelets via Wrapping. This method utilises application of USFFT for Curvelet Transform calculation. The discrete curvelet transform using USFFT is implementedin following four steps:

Algorithm 5 :FDCT Using USFFT

1: Apply the 2D FFT and obtain Fourier samples $f[n_1, n_2], -n/2 <= n_1, n_2 < n/2$

2: For each scale/angle pair (j, l), interpolate $f[n_1, n_2]$ to obtain sampled values $f[n_1, n_2 - n_1, tan\theta]$ for $(n_1, n_2) \in P_j$

3: Multiply the interpolated object f with the parabolic windowU_j, effectively localizing f near the parallelogram with orientation θ and obtain

$$f[n_1, n_2] - f[n_1, n_2 = n_1 tan\theta]U_j[n_1, n_2] \tag{1.4}$$

4: Apply the inverse 2DFFT to each $f_{j,2}$ which generate the discrete coefficients $c^D(j, l, k)$

The fast discrete curvelet transform is simpler,faster and less redundant. This method utilises a decimated rectangular grid which is tilted along the main direction of each curvelet.

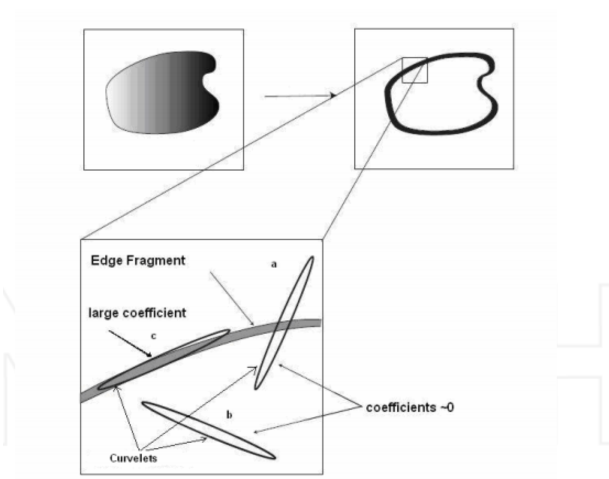

Figure 1.9: Schematic diagram to present the curvelet coefficient extraction from edge of the image

1.4.2 Proposed Algorithm

The curvelet transform for feature extraction begins with application of 2D FFT on the imagefrom which wedges are identified. The parabolic shape of wedges comes from the partitioning the Fourier plane into radial (concentric circles) and angular divisions. The concentric circles are used to divide the image into multiple scales while the angular divisions partition the bandpassed image into different angles. So every single wedge is specifically identified by it scale and orientation . This indicates that the inverse FFT of a particular wedge if taken, will determine the curvelet coefficients for that scale and angle. This is the main idea behind the implementation of curvelet transform. Figure 1 (right) represents curvelets in spatial Cartesian grid associated with a given scale and angle. The proposed algorithm consists of a process of applying FDCT on to the face image database followed by feature extraction and then recognition.

Algorithm 6 :Curvelet Transform for Feature Extraction

1: Calculate FDCT coefficients of the face image

2: Store these as the features ectracted from the image

3: Apply the Steps 1&2 to each face image in the gallery set and test set followed by storing the feature file

4: Calculate the Euclidean distance between the test image feature vector and each of the training image feature vectors.

5: The training image with the minimum Euclidean distance to the test feature vector is the correct face. (For verification applications, the Euclidean distance must be below a set threshold)

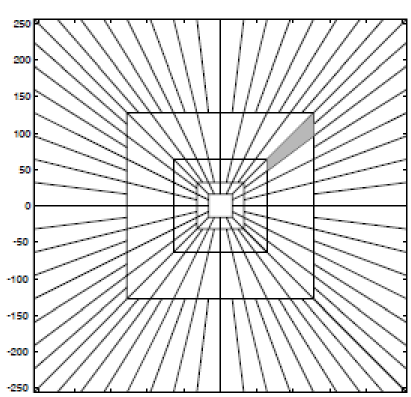

Figure 1.10: Basic digital tiling. The windows localize the Fourier transform near the sheared wedges obeying the parabolic scaling.

1.5 Implementation Results

The experiment is conducted to find the features of the face image by application of gabor transform,curvelet and ridgelet separately on a set of data known as gallery images. In order to have a dataset possessing more than one face image for a particular person, FERET database has been put to use. The FERET database consist of around 739 users each of which have multiple images taken in different oreintations and different expressions. This experiment is limited to application of filters and extraction of feature only from normal front faces of the users. The CASIA-Face V5 has 500 subjects & 5 images per user.These images are first converted to gray-scale as part of pre-processing and then the transforms are applied for feature extraction. The Yale database has 165 grayscale images of 15 individuals andeach person has 11 images. So, from every database a dataset is selected of diffrent sizes taking into consideration the size factor of the database and hence the speed of the program. In this dataset, the users have been assigned numbers and their respective images are re-named in the format $< User_I d >_{<} Image_I d >$. The features when extracted are also named in the similar way.It is ensured that each user has equal number of images.

1.5.1 Experimental Setup

To carry out the expermient, n users are randomly selected from different face databases (FERET, CASIA, Yale) and these are the gallery images. Gabor filter is applied to each of these images to extract the features and store them in respective images' file. Out of these gallery images, a specific number of users are selected at random that act as probe images. Each of these probe image is matched agianst each gallery image in order to find the matching individual. Similar process is re-applied for the ridgelet transform. The reliability of these filters is determined by measuring the False Rejection Rate and False Acceptance Rate of each of these filters for different experiments carried out on databse of same size. *False Acceptance Rate* is calculated as the number of instances when non-matching individuals' face images turn out to be matched per number of images in the gallery.

False Rejection Rate is calculated as the number of instances when matching individuals' face images turn out to be not matched per number of images in the gallery.

1.5.2 Result

Table 1.1: Recognition Rate (in percent)

Feature Extraction Method	Expt no. 1	2	3	4
$Wavelet\ Transform(FERET)$	0.82	0.83	0.86	0.78
$Curvelet\ Transform$	0.89	0.90	0.86	0.87
$Wavelet\ Transform(CASIA - FaceV5)$	0.76	0.88	0.78	0.86
$Curvelet\ Transform$	0.84	0.84	0.88	0.92
$Wavelet\ Transform(Yale)$	0.53	0.69	0.59	0.67
$Curvelet\ Transform$	0.73	0.80	0.67	0.67

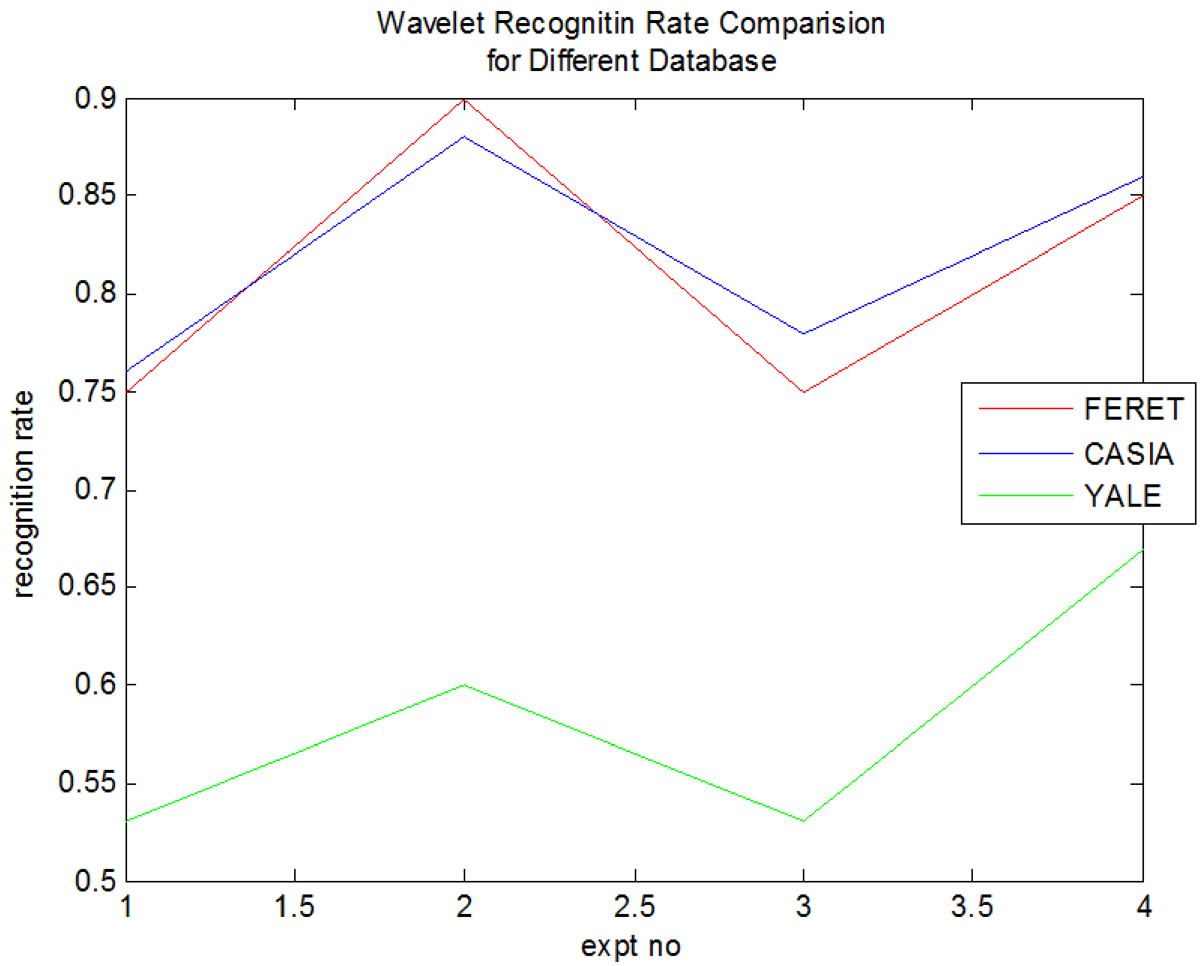

Figure 1.11: Wavelet Recognition Rate Comparision

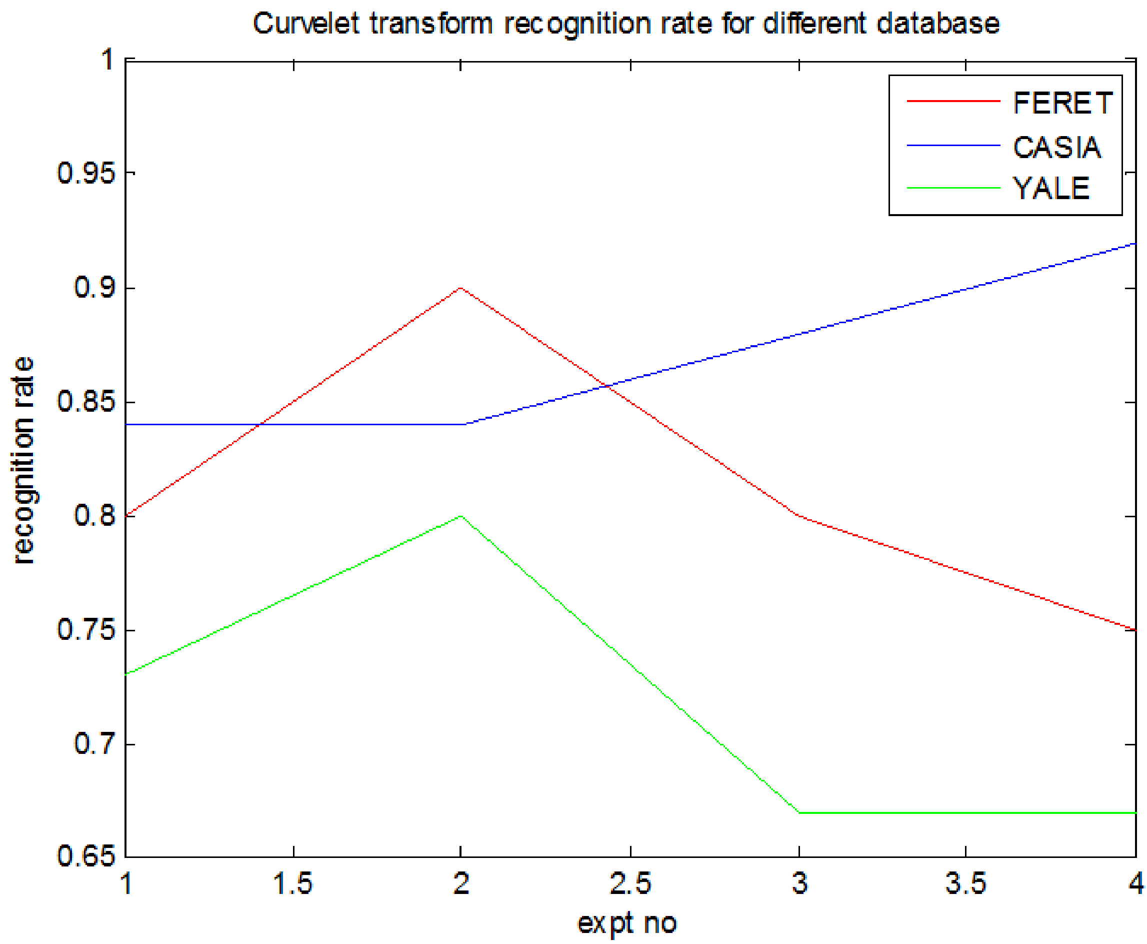

Figure 1.12: Curvelet Recognition Rate Comparision

Chapter 2

DOST Based Feature Extraction For Face Recognition

The Stockwell transform (ST) is a recently proposed multiresolution transform that supplies the absolutely-referenced frequency and phase information unlike Wavelet Transform which has provisions for only scale information.[9] However, the ST redundantly doubles the dimension of the original data set. Due to this redundancy presented by ST, it becomes computationally expensive and even infeasible on some large size data sets. Therefore, an improved method namely discrete orthonormal Stockwell transform (DOST), a non-redundant version of ST is used and implemented for face feature extraction.This method can be applied for feature extraction since DOST is useful in image compression and image restoration.So, is one of the best methods to extract face features for recognition purpose.

2.1 Why S-Transform?

The discrete wavelet transform have a complexity of O(N), where N = size of input. But this transform takes into account the scale factor of the image for feature extraction which does not refer to the frequency in true sense. And there is no straightforward way to turn this scale information into proper frequency information. This is made possible in stockwell transform which takes the absolute frequency component of the image.

2.2 Theory

DOST transform eliminates the redundant nature of S-Transform ad hence provides a lower time complexity.[8]It provides the spatial representation similar to DWT.It has the additional benefit of maintaining phase properties of S-Transform & Fourier Transform. It also eliminates the redundancy in space frequency domain.The 1D-DOST transform works by:

Creating a set of N orthogonal unit-length basis vectors in Complex Plane, where each vector targets a particular region in time frequency domain. Each region is defined by following 3 parameters:

$\nu = Centerofeachfrequencyband$

$\beta = Widthofthatband$

$\tau = Locationintime$

For each of these parameters, we have a kth basis vector which is given as:

$$D[k]_{[\nu,\beta,\tau]} = \frac{1}{sqrt\beta} \sum_{f=\nu-\frac{\beta}{2}}^{\nu+\frac{\beta}{2}+1} e^{-i2\pi\frac{k}{N}} e^{-i2\pi\frac{\tau}{\beta}} e^{-i\pi\tau} \tag{2.1}$$

The DOST coefficient is given by the dot product of the value in the vecto at k position whose DOST is required and the k^{th} basis vector which is calculated by the above formula.Each frquency band has 2^{p-1} basis vectors. Here the co-efficients decompose really fast and hence have low time complexity as a result of which this method has an advantage over S-transform. S-transform has time complexity of $O(N^4)$ while DOST has the improvement and has $O(N^2)$ complexity. S-transform and DOST generate exactly same results but the program execution time becomes really high as the dimension of the input vector increases.

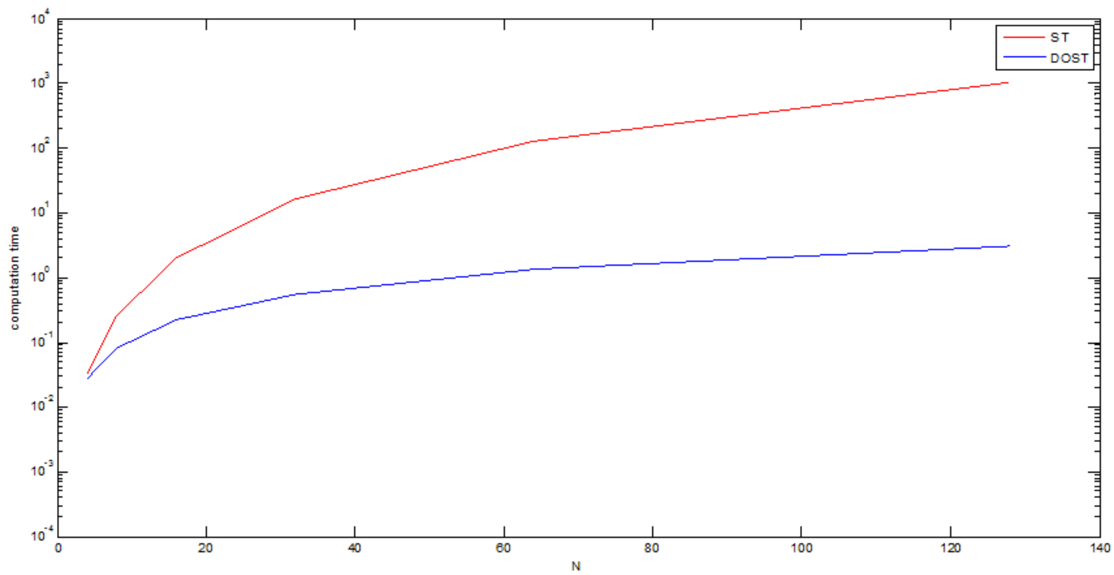

Figure 2.1: Time complexity comparision between ST and DOST

2.3 Proposed Algorithm

In order to apply this transform to image files, it is necessary thet the transform should be compatible to work with a 2 dimensional matrix. Hence we devise a method to implement 2D-DOST onto image and the values retrieved are then stored as extracted features of the corresponding face images. The proposed algorithm consists of applyiing 2D-DOST to the face image in order to get the 2D-DOST coefficients. The steps involved in calculation of 2D-DOST coefficients are summarised in the following algorithm.

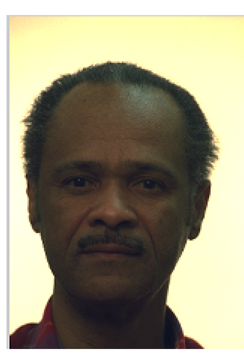

Figure 2.2: Example input image

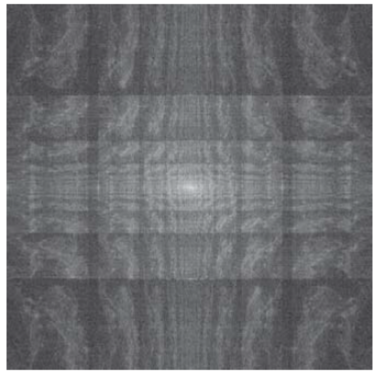

Figure 2.3: Logarithm of DOST coefficients of the image

Algorithm 7 :2D-DOST Coefficient Calculation

1: Calculate 1-D DOST coefficients for row-wise arrays of input image and stored in an array having the intermediate coefficients matrix

2: Calculate 1-D DOST coefficients are calculated for column-wise arrays from the intermediate coefficient matrix.

2.4 Experimental Evaluation

2.4.1 Datasets

The experiment is conducted to find the features of the face image by application of discerete orthogonal S-transform separately on a set of data known as gallery images. In order to have a dataset possessing more than one face image for a particular person, FERET database has been put to use. The FERET database consist of around 739 users each of which have multiple images taken in different oreintations and different expressions. This experiment is limited to application of filters and extraction of feature only from normal front faces of the users. So, from every database a dataset is selected of diffrent sizes taking into consideration the size factor of the database and hence the speed of the program. In this dataset, the users have been assigned numbers and their respective images are re-named in the format $< User_I d >_< Image_I d >$. The features when extracted are also named in the similar way.It is ensured that each user has equal number of images.

2.4.2 Experimental Setup

To carry out the expermient, n users are randomly selected from face database (FERET) and these are the gallery images. DOST is applied to each ofthe images to generate the feature file. The reliability of these filters is determined by measuring the False Rejection Rate and False Acceptance Rate of each of these filters for different experiments carried out on databse of same size. *False Acceptance Rate* is calculated as the number of instances when non-matching individuals' face images turn out to be matched per number of images in the gallery.

False Rejection Rate is calculated as the number of instances when matching individuals' face images turn out to be not matched per number of images in the gallery.

2.4.3 Results

The application of DOST onto face images of FERET database reveal that the recognition rate is much better than the Wavelet and curvelet transform.The following table reveals the low values of FAR and FRR and hence presenting a better and sound method for recogntion of face.

Table 2.1: DOST results

Experiment No.	GallerySize	FAR	FRR
1	150	0.0296	0.0185
2	200	0.0145	0.0164
3	250	0.0086	0.0138
4	300	0.0053	0.0123

The table displays that as the size of the gallery increases the rate of error in false rejection and false acceptance also decreases. It also clarifies that the error rate is very less or negligible as compared to other methods used for feature extraction.The comparision between the error rate that is observed from the three methods of feature extraction.

Method for feature extraction	FAR	FRR	Recognition Rate (Accuracy)
Wavelet Transform	0.0985	0.0798	82.77%
Curvelet Transform	0.0565	0.0456	89.80%
DOST	0.0296	0.0185	95.19 %

Figure 2.4: Comparision of results

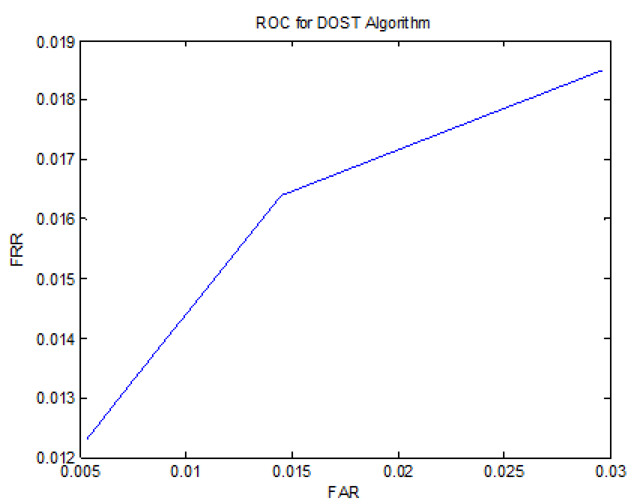

Figure 2.5: ROC curve for DOST

Chapter 3

LDA Based Feature Extraction

Extracting features from face images for detection and recognition purpose is a central issue for face recognition system. Out of all approaches available at hand, those based on appearance are consdered to be most favourable.Although feature extraction methods provide us with the main features that are associated with the face image sufficient enough to make good recognition, the feature set produced by these methods have very large dimension as a result of which a standard image of size 128×128 generates 16384 values of features which is even greater than the number of training sets that are put into use. Thereforemethods like PCA and LDA are used for dimensionality reduction and hence can provide efficient matching of features of faces for recognition purpose.In this chapter, Linear Discriminant Analysis (LDA) has been implemented on the DOST features in order to reduce the dimensionality and hence make the matching proocess done via euclidean distance a faster process.Here, LDA is used for multi-classification since the gallery contains face images of multiple users and recognition aims at classifying the face image into one of the many user classes available.

3.1 LDA for 2-Class

LDA for 2 classes was introduced by Fisher in 1936. The main idea behind this method was to convert the multi-attribute variable x into mono-attribute observations y such that the resultant observations are clearly distinct. For example, there are N m-dimensional samples $x_1, x_2, ..., x_N$, where $x_i = (x_{i_1}, , x_{i_m})$ belonging to two different classes, namely c_1 and c_2.For each of the class their matrix is given as:

$$S_i = \sum_{\mathbf{x} \in c_i} (\mathbf{x} - \bar{x_i})(\mathbf{x} - \bar{x_i})^T \tag{3.1}$$

,where $\bar{x_i} = \frac{1}{m_i} \sum_{\mathbf{x} \in c_i} \mathbf{x}$ and m_i is number of items present in Class c_i . Hence, total intra-class matrix is:

$$S_w = S_1 + S_2 = \sum_i \sum_{\mathbf{x} \in c_i} (\mathbf{x} - \bar{x_i})(\mathbf{x} - \bar{x_i})^T \tag{3.2}$$

And total inter-class scatter matrix is given as:

$$S_b = (\bar{x_1} - \bar{x_2})(\bar{x_1} - \bar{x_2})^T \tag{3.3}$$

. The classification is done such that the ratio of determinant of the inter-class matrix to that of intra-class matrix is maximized.i.e:

$$F(\phi) = \frac{|\phi^T S_b \phi|}{|\phi^T S_w \phi|} \tag{3.4}$$

If S_w is non-singular , then it can be solved as a simple eigen-value problem.

3.2 LDA for Multiple-Class

For face recognition purpose the number of classes is more than 2.[7] This is an extension of the 2-class LDA method. In 2-cass case, high demensional data is projected onto a low-dimensional data which is then decided to belong to one of the 2 classes. But in case of multi-class, the decision needs to be taken among several classes.For example, there are k classes of users present. Then the intra-class matrix is given as:

$$S_w = S_1 + S_2 + ... + S_k = \sum_{i=1}^{k} \sum_{\mathbf{x} \in c_i} (\mathbf{x} - \bar{x_i})(\mathbf{x} - \bar{x_i})^T \tag{3.5}$$

The inter-class scatter matrix is as:

$$S_b = \sum_{i=1}^{k} N_i (\bar{x_i} - \bar{x})(\bar{x_i} - \bar{x})^T \tag{3.6}$$

.

where N_i is the number of training samples for each class, x_i is the mean for each class and $\bar{x}$ is total mean vector given by $\bar{x} = \frac{1}{N}\sum_{i=1}^{n} m_i \bar{x}_i$. After getting S_b and S_w, the linear transformation ϕ is to be maximized to obtain the classification. To reduce the computational cost for large data-sets, the following equality can be used:

$$S_b u_i = \lambda_i S_w u_i$$

where u_i and λ_i arethe eigenvectors and eigenvalues of $\{S_b, S_w\}$ In order to reduce the dimension from n to m,Then m highest eigenvectors and eigenvalues are chosen and the matrix is reconstructed. 50% reduction is implemented

3.3 Classification

Once the transformation function ϕ is available, the classification is then done using :
Euclidean distance $d(x, y) = \sqrt{(}\sum_i (x_i - y_i)^2)$ and
Cosine measure $d(x, y) = 1 - frac \sum_i x_i y_i \sqrt{(}\sum_i (x_i)^2) \sqrt{(}\sum_i (y_i)^2)$.
Then using these similarity measures the classification can be done easily and in less time as compared to the methods which implement only feature extraction without dimensionality reduction.

3.4 Experimental Evaluation

3.5 Datasets

The experiment is conducted to find the features of the face using discerete orthogonal S-transform separately on a set of data known as gallery imagesfollowed by dimensionality reduction using LDA. In order to have a dataset possessing more than one face image for a particular person, FERET database has been put to use. The FERET database consist of around 739 users each of which have multiple images taken in different oreintations and different expressions. This experiment is limited to application of filters and extraction of feature only from normal front faces of the users. In this dataset, the users have been assigned numbers and their respective images are re-named in the format $< User_Id >_<$ $Image_Id >$. The features when extracted are also named in the similar way.It is ensured that each user has equal number of images.

3.6 Experimental Setup

Out of these gallery images, a specific number of users are selected at random that act as probe images. Each of these probe image is matched agianst each gallery image in order to find the matching individual. DOST is applied to generate the features and then LDA is carried out in each class to help in dimensionality reduction.LDA reduces the multivariate samples by half the number of features that make them easy to classify.

3.7 Results

The accuracy of matching via Euclidean distance method for the reduced feature vectors obtained from face database FERET. The dataset chosen for gallery contains $N = 30, 40, 50, 60$ user classes each containing 5 samples of size 64×64.5 Images are chosen randomly to be used as probe set. The experimental results shown for DOST and DOST followed by LDA are shown as:

Table 3.1: DOST and DOST+LDA Comparision results

Expt No.	No.Class	FAR(DOST)	FRR(DOST)	FAR(DOST+LDA)	FRR(DOST+LDA)
1	30	0.0296	0.0185	0.0305	0.0246
2	40	0.0145	0.0164	0.0216	0.0176
3	50	0.0086	0.0138	0.0185	0.0190
4	60	0.0053	0.0123	0.0096	0.0185

The LDA method,although provides a slightly higher error rate but the time involved in classification of data is considerably small and hence can be put into practical use for face recognition in collaboration with DOST.

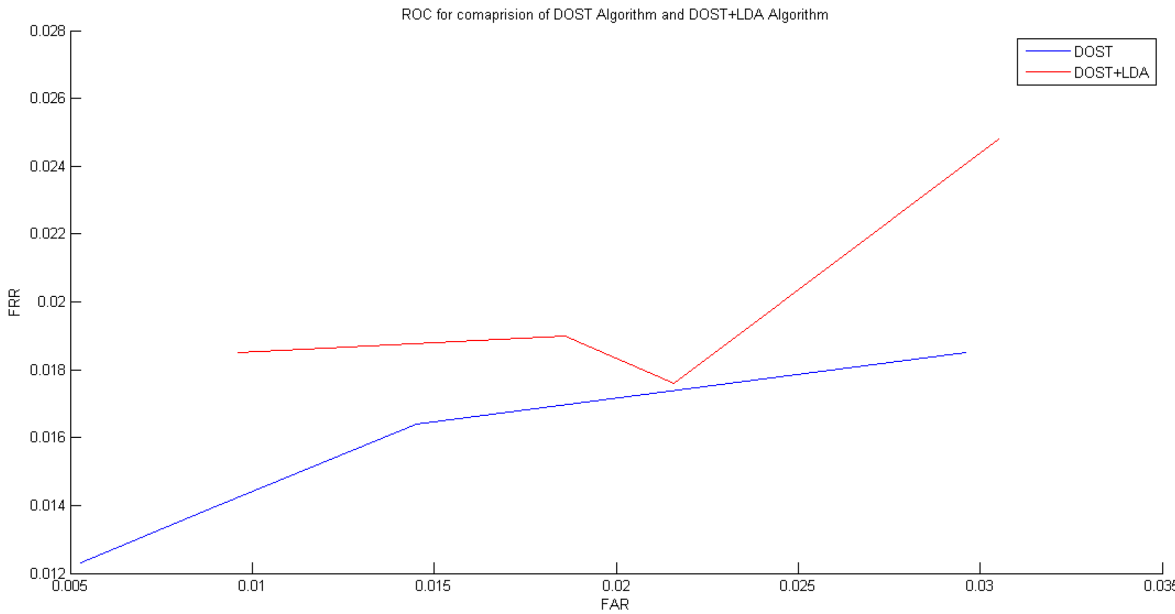

Figure 3.1: ROC curve for DOST and DOST+LDA

Chapter 4

Conclusion

This paper develops technique to extract the features vector of the whole face in image DB by using Gabor filters which are known to be invariant to illumination and facial expression.We introduce 8 different orientations and 5 different resolutions to extract the maximum of information, to reduce the dimension of the result vector, we apply sparse random projection, it provides many advantages: it is easy to implement, fast and more effective when compared toother methods. Euclidean Distance is then applied to perform the recognition task. Our network achieves higher recognition rate and better classification efficiency when the feature vectors have low-dimensions.

Here it is also explained how the Radon transform extracts the directional features of the image very accurately. At the same time, the wavelet transform keeps the system computationally efficient, robust and illumination resistant. Additionally, it enhances the computational speed and accuracy of the whole system. Using the ridgelet transform in the development of the algorithm is beneficial in the sense that it is highly efficient for line or plane singularities. From the given observations it can be easily concluded that DOST transform provides the spatial representation similar to DWT and its additional benefit of maintaining phase properties of S-Transform & Fourier Transform and better recogntion rate make it a method better as compared to the previously implemented methods.DOST followed by LDA provides an accurate and a time efficient method which seems acceptable to be used for practical purposes.

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