

# Face Verification for Security in Videos: Set Estimation and Class Specific Thresholds

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## Abstract

In conventional still face recognition techniques, any query image is always classified to one of the face classes irrespective of whether the query image is a face or not. Most of the recognition algorithms are dissimilarity based, and one needs to put a proper threshold on the dissimilarity value for the sake of classification. In this paper, we introduce a novel thresholding technique for classification for the video-to-video face frames. The theoretical formulation of the thresholding technique and its utility are demonstrated on each of the probe videos for still-to-video and video-to-video set. The proposed threshold selection is based on statistical method of set estimation and is guided by minimal spanning tree. It has been found that the proposed class specific threshold technique performs better than the other methods of threshold selection for videos.

*Keywords:* Feature extraction, Minimal spanning tree, Intra-class specific threshold, Set estimation, FAR, FRR

## 1. Introduction

Traditional face recognition techniques [1, 2] may work well when applied on the still face image database. However, recognition from video streams needs special attention due to unconstrained variations of pose, illumination, selection of the key frames, resizing of area of interest. A fast and automatic way of achieving such a real time task is to put a class specific threshold on the dissimilarity value at the verification stage. On the basis of the decision threshold, a biometric recognition system should be in a position to accept the query image as client or reject it as imposter. The selection of proper threshold of a given class in a dataset is an open question, as it is related to the difficulty levels dictated in face recognition problems. Difficulty levels are likely to change from situation to situation in case of video surveillance. In a face recognition problem for an ideal security system, three difficulty levels may be ascertained. These are (i) zero effort attack, (ii) minimal effort attack and (iii) organized effort attack [6]. In zero effort attack, a person tries to enter a security system unknowingly when he puts no effort to fool the system. In a minimal effort case, a person puts in some effort, make-up etc., to fool the system. In the last case, a person puts in enormous effort in an organized manner to break into the system. Depending on the demand imposed on security system, the difficulty levels are decided. In the current problem we are interested in finding the threshold values for detection for the facial classes when the attacks are with zero effort.

In video to video face verification [3, 4], the frames are first extracted from both the gallery and probe videos. Then the features are extracted from the still frames and the Euclidean distance between gallery and probe is calculated. For probe classification mostly

the nearest neighbor [18, 19] or minimum distance classifiers are used. As in still-to-still face recognition, a popular way for video face classification is to form the face space using any of the dimensionality reduction techniques [1, 2]. To avoid the curse of dimensionality the image space is converted to face space and each gallery face frame is transformed to a face point in the face space. In case of video the difference in information in two consecutive frames in a video is small (except for the presence of a key frame), and hence the intra personal variations are smooth. Due to this property the inter cluster distances of the face points of different classes should be larger than the distances of intra class face points. Thus the use of class specific thresholds for gallery face frames is appropriate in this context, and it may result in increasing the speed of the recognition method.

Literature shows that both the still to still and video to video biometric authentication methods [6, 7, 8] are similar in nature. Most of the video face recognition systems are based on the closed set, the classical approach of verification where the test face always exists in the client database. However, in a real life scenario the identification system may face a situation where the query face image may not be present in the database, i.e. often referred by the biometric researchers as the open set identification. In the current problem we are interested in finding proper threshold values for the face classes which can be used for both open and closed set identification.

As in the literature the threshold value is determined using receiver operating characteristic (ROC) curve which in turn, is based on the different values of false acceptance rate (FAR) and by false rejection rate (FRR) [8] discussed by Mansfield et al [9]. The point on the ROC curve that satisfies the condition of the equal error rate (EER), when FAR = FRR, is selected as the operating threshold for subsequent tests. Finding a good estimate of FAR is not always possible, because in reality, a system can have extremely few examples of genuine access and relatively few imposter accesses as found in the literature. As a result user specific threshold selection is very unreliable to involve FAR and FRR. Again the common practice is to use the global threshold for a system rather than using user dependent versions of ROC. Another way of putting class specific priori threshold is suggested by Padilha et al [10] for the video face sequences.

In the current problem we are interested in finding the threshold values using set estimation method, for the facial classes of the gallery video frames. The set estimation method has been tackled by several authors in literature [11, 12, 13, 14, 15]. The method of set estimation is mainly used to find the pattern class and its multivalued shape/boundary from its sample points in the two dimensional feature space  $\mathbb{R}^2$  [11]. Some investigation on estimation of  $\alpha$ -shapes for point sets in  $\mathbb{R}^3$  had been proposed by Edelsbrunner [12] later Mandal [13, 14] extended the method to  $\mathbb{R}^m$  dimensions and found it very useful in developing a multivalued recognition systems. As one can get the shape or boundary of a given set then that procedure of set estimation also generates the intuition for determination of the class thresholds of the set. As a tool of set estimation, minimal spanning tree (MST) is proposed to calculate threshold value [11]. In this paper we propose user specific threshold for the video face sequence in a well known VidTIMIT database [17]. For the purpose of reducing the dimensionality, we need to extract features by using any one of the subspace methods. The feature extraction methods are explored here namely principal component analysis (PCA) in frequency domain. The magnitude spectrum has several advantages in case of video face recognition because of its shift invariant nature.

The paper is organized in five sections. After an introductory section, Section 2 deals with the mathematical preliminaries of the set estimation method. Section 3 contains the

threshold incorporated face classification using set estimation method. Section 4 contains the proposed method of intra class threshold calculation for facial classes, Section 5 is for verification and results analysis.

## 2. Mathematical Preliminaries for Threshold Selection

The intuition for the proposed threshold selection mechanism is provided in the next subsection. We assume that the feature extraction step has already been carried out either in spatial or in the frequency (magnitude) domain using any subspace method.

### 2.1 Intuition for The Method

In each class of the video database we may have large number of frames containing smooth changes, such as video frames of same person having different expressions with smooth changes as temporal information. The images of the same person, giving the same expression at different times, may differ even if the lighting and other peripheral conditions remain invariant. This is due to the fact that, for the same expression, there may be different small changes in muscle movements in face video. For example, movement of eye brows, different locations of iris, twitching of nose, different muscle movements in cheeks and mouth portions etc. Let us assume that we have  $n$  images corresponding to a particular expression  $P$  of a particular person. Note that, for the same expression  $P$ , the corresponding set, intuitively, is to be connected too since for two different chosen frames of the same expression, we must be able to provide the intermediary frames of that expression (a path connecting the two points is completely contained in the set.). If we represent an image of an expression of  $P$  by a vector  $x_0$  then the set corresponding to the small variations in the same expression may be assumed to be a disc of radius  $\epsilon > 0$  around  $x_0$ . The set corresponding to an expression of the same person  $P$  may be taken as  $\bigcup_{i=1}^n x \in \mathfrak{R}^m : d(x_i, x) \leq \epsilon$  where  $x_1, x_2, \dots, x_n$  are the  $n$  vectors corresponding to the given  $n$  images of the same expression for the same person and the dimension of the vectors is assumed to be  $m$ . The set corresponding to the union of all possible expressions of a person may also be taken as a connected set. The face class of a person is nothing but the set of all possible expressions of that person.

### 2.2 Mathematical Formulation of Threshold

A general formulation of the face class, probably, would have the radius value depending on the center of the disc. Here, that possibility is not considered because of the complicated nature of the formulation. The radius value is taken to be independent of the the center of the disc here. In the above formulation, as the number of face images of the same person increases, we shall be obtaining more information regarding the face class, and hence the radius value needs to be decreased. Thus the radius value needs to be a function of the number of images. Usually one may want to "estimate" a set on the basis of the given finitely many points. Grenander has formulated the set estimation problem as the problem of finding consistent estimate of a set [15].

**Definition.** Let  $X_1, X_2, \dots, X_n$  be a sequence of independent and identically distributed random vectors which follow some continuous distribution over the set  $\alpha \subseteq \mathfrak{R}^m$ , where  $\alpha$  is an unknown quantity. Let  $\alpha_n$  be an estimated set based upon the random vectors  $X_1, X_2, \dots, X_n$ . Then  $\alpha_n$  is said to be a consistent estimate of  $\alpha$ , if  $E_\alpha[\mu(\alpha_n \Delta \alpha)] \rightarrow 0$  as  $n \rightarrow \infty$ , where  $\Delta$  denotes symmetric difference,  $\mu$  is the Lebesgue measure and  $E_\alpha$  denotes the "expectation" taken under  $\alpha$ .

**Result.** Let  $X_1, X_2, \dots, X_n$  be independent and identically random vectors, which follow uniform distribution over  $\alpha \subseteq \mathfrak{R}^2$  where  $\alpha$  is unknown. Let  $\alpha$  be such that  $cl(Int(\alpha)) = \alpha$

and  $\mu(\delta\alpha = 0)$  where  $\delta\alpha$  denotes the boundary of  $\alpha$ ,  $cl$  denotes closure, and  $Int$  denotes the interior. Let  $\{\epsilon_n\} \rightarrow 0$  be a sequence of positive numbers such that  $\epsilon_n \rightarrow \infty$  and  $n\epsilon_n^2 \rightarrow \infty$  as  $n \rightarrow \infty$ . Let

$$\alpha_n = \bigcup_{i=1}^n \{x \in \mathbb{R}^2 : d(x, X_i) \leq \epsilon_n\} \quad (1)$$

where  $d$  denotes the Euclidean distance. Then  $\alpha_n$  be a consistent estimate of  $\alpha$ .

**Remarks.** (i) The above result did not mention a way of finding  $\epsilon_n$ . (ii) The intuition, which was discussed earlier, is reflected in equation 1. (iii) There are several sequences of  $\{\epsilon_n\}$  which provide consistent estimate. Thus, one needs to choose the radius judiciously.

Murthy [11] developed a way of finding  $\{\epsilon_n\}$  for points in two dimensional spaces. He also generalized the method to any continuous density function on  $\alpha$ , where  $\alpha$  is a path connected set. His method, its applications in different fields, and a few of its modifications are well documented in literature [11, 12, 13, 14].

### 3. Threshold Incorporated Face Classification Using Set Estimation Method

In the present problem, a dimensionality reduction method is implemented initially. It is followed by the set estimation method. The estimated set is to be path connected and connectivity is preserved by MST. There are several ways in which we can make the estimated set connected. We shall describe a generic way of making the estimated set connected, where only finite union of disks is considered.

**Method.** (a) Find minimal spanning tree (MST) of  $S = \{X_1, X_2, \dots, X_n\}$  where the edge weight is taken to be the Euclidean distance between two points.  $S$  is a finite set of points  
 (b) Take  $\epsilon_n$  as maximum of the  $(n - 1)$  edge weights of MST.  
 (c) Take the estimate  $A_n$  as

$$A_n = \bigcup_{x \in S} \{y : d(x, y) \leq \epsilon_n\} \quad (2)$$

$\epsilon_n$  is not dependent on the dimension  $m$ .

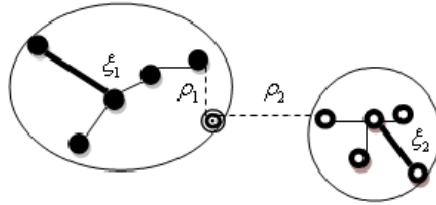
The reason behind choosing the above is given here. Note that, if we take as maximum of the  $(n-1)$  edge weights,  $A_n$  would be path connected. Note also that, in order to have the connectivity of the graph,  $\epsilon_n$  is to be at least the maximum of  $(n-1)$  edge weights.

To establish the usefulness of the above method in face classification problem, several face images for the same human being are considered. The number of classes is same as the number of human beings. Let us consider  $M$  human beings and for each human being we have  $N$  face images of same size and same background. If we represent an image by a vector  $x$ , then we are considering all possible such vectors corresponding to a human being. Let us represent such a set by  $\alpha$ . This set denotes the face class of that human being. Only a few points of  $\alpha$  like the different expressions of a face are known to us. Initially we apply one of the feature extraction methods described earlier to reduce the number of dimensions for  $m$ . Thus every face now is an  $m$  dimensional vector. For every one of  $M$  human beings, we have  $N$  number of such  $m$  dimensional vectors.

### 3.1 Local Threshold Based Recognition Method

We assume that we have  $M$  classes, each class denoting a human being. Each class consists of  $N$  vectors of  $m$  dimensions. Here for each class we calculate MST of the respective  $N$  vectors and find its maximal edge weight. Let us denote the maximal edge weight of the MST of the  $i^{th}$  class by  $\xi_i$  for any  $m$  dimensional vector  $x$  in the following way. The recognition method is described as:

1. The total number of given vectors is  $MN$ . For each class  $i$ , find the minimum distance of  $x$  with all the  $N$  points in the class. Let the minimal distance be  $\rho_i$
2. If there exists an  $i$  such that  $\rho_i \leq \xi_i$  then put  $x$  in the  $i^{th}$  class.
3. If there does not exist any  $i$  such that  $\rho_i \leq \xi_i$  then the given image does not fall in any one of the given face classes.



**Fig. 1:** Explanation for  $\xi_1, \xi_2$  and classification.

The process of applying local thresholds is depicted in Fig. 1 where black discs denote points in training set from class 1. Black discs with holes denote points in training set from class 2.  $\xi_1$  is the maximal edge weight of 4 edges of MST of 5 points in class 1.  $\xi_2$  is the maximal edge weight of 4 edges of MST of 5 points in class 2. The point with rings is the point to be classified. Its nearest neighbor is at a distance  $\rho_1$  from class 1, where  $\rho_1 \leq \xi_1$ . Note that the nearest neighbor of that point from class 2 is at a distance  $\rho_2$  from it, where  $\rho_2 > \rho_1$  and  $\rho_2 > \xi_2$ . Thus, that point will be classified to class 1.

## 4. Experimental Design and Result Analysis on Video Face Database

### 4.1 Video Face Dataset Description

The proposed method of threshold based classification has been used for face recognition and tested over the VidTIMIT dataset [17] was created for both audio and video applications. The recorded dataset allows for changes in the hair style, clothing and mood. Additionally, the zoom factor of the camera was randomly perturbed after each recording. The creators of the data set considered 43 volunteers (19 female and 24 male). For each volunteer, a folder is created. Thus there are 43 folders. Each folder has an audio part and a video part. Each such video has minimum two subfolders and maximum eight sub folders. But each such video has two subfolders common to all of them. They are ‘head’ and ‘sa1’. The ‘head’ folder does not have any speech component in it. It has frames containing movement of head to the left, right, back to the center, up, then down and finally returns to center. Except head movement, there is no change in the appearance of the volunteer in the ‘head’ folder. The ‘sa1’ folder contains the frontal face frames with mouth and eye movements of a volunteer. From the whole dataset only the ‘head’ folders and ‘sa1’ folders for each person are selected. The other sub-folders are not considered since they are not available for

each person. All the video frames have single person with same background. No tracking method is applied. Before inputting the frame gallery and probe frames the face portions are manually cropped to dimension 64X64 for each of 43 classes and all the color frames are converted to gray. To form the face space from the image space we have used the simple principal component analysis (PCA) on magnitude in Fourier domain. PCA with nearest neighbor classifier is compared with the proposed class specific threshold based classifier method.



**Fig. 2:** Selected face frames of a subject in VidTIMIT database: ‘head’ folder (up) and ‘sal’ folder (below).

#### 4.2 Formation of Frequency Domain Magnitude Face Space

The face image data is typically represented in a very high dimensional space hence the dimension needs to be reduced. Several techniques have been proposed in the literature as PCA (principal component analysis), LDA (linear discriminant analysis), kernel PCA etc. These methods are widely applied on spatial domain. The concept of applying these methods for the still images in frequency domain is discussed [16].

For PCA application in frequency domain, required reduced dimension of the face space can be achieved by the highest  $m$  eigenvalues of the eigenproblem given by

$$S_f w_f = \lambda_f w_f \tag{3}$$

where  $\lambda_f$  is the eigen value and  $w_f$  is the corresponding eigenvector and the covariance matrix is  $S_f$  in the Fourier domain. The eigenvalue problem in Fourier space is given by

$$S_f = \frac{1}{n} \sum_{i=1}^n F(x_i - \mu) F(x_i - \mu)' \tag{4}$$

where  $F$  is two dimensional Fourier transform.  $x_i$  is the  $i_{th}$  face frame,  $\mu$  is the mean of face frames, and  $n$  is the total number of face frames in the gallery.

If the faces in gallery videos are shifted due to the head movement etc, that shift will translate into a linear phase change in frequency domain but that will not effect on the magnitude. In case of videos these kind of shift can occur very often. So the extracted magnitude spectra in frequency domain makes the system robust and with less error. Among the 43 subjects, we have taken first 20 subjects for this experiment. For each subject, 10 consecutive frames are chosen in the training set, and the next consecutive 200 frames of each class are used as test set.

#### 4.3 Threshold Based Close and Open Set Identification Method

The proposed method derives user specific thresholds. The probe and the gallery frames are projected to the Fourier face space and from the gallery face point the user class specific

**Table 1:** Formation of face space.

Database	VidTIMIT	Number of subjects in video	Number of frames / subject	Reduced Dimension of face space in frequency domain
head folder		20	10	180
sa1 folder		20	10	180

**Table 2:** Comparison of proposed method with PCA and nearest neighbor and minimum distance classifier.

Database	Folders Used	PCA with Nearest Neighbor classifier	PCA with Minimum Distance Classifier	Proposed Method with local threshold
head folder		91 %	92 %	95 %
sa1 folder		94 %	93.5 %	97 %

thresholds are derived by the proposed method discussed in Section 3. The face frame may be put in more than one class according to the proposed formulation. In such a case, to get unique classification, we used the nearest neighbor (NN) [18, 19] and minimum distance classifier rule for all those classes to which the frame is classified. Nearest neighbor (NN) classifier (parameter free classifier) and minimum distance classifier are used to compare with the proposed method where the class specific threshold values are used for identification. It is observed from Table 2 that the recognition rate with threshold performs better than the non threshold based systems.

**Test of significance:** From Table 2, the proposed method is found to give better results than the usual NN classifier. Additionally, we checked whether the performance of the proposed method is significantly different from the other. We employed the z-test for the equality of proportions. The test statistic is

$$a = \frac{p_1 - p_2}{\sqrt{p(1-p)\left(\frac{1}{n_1} + \frac{1}{n_2}\right)}} \quad (5)$$

where  $p_1 = \frac{x_1}{n_1}$ ,  $x_1$  is the number of correctly classified images out of  $n_1$  images using the PCA NN classifier and  $p_2 = \frac{x_2}{n_2}$ ,  $p = \frac{x_1 + x_2}{n_1 + n_2}$ .

The observed value of  $a$  is 8.3. This observed value lies outside not only the 95 confidence interval (-1.96, 1.96) but also the 99% confidence interval (-2.575, 2.575). Thus, we reject the hypothesis that the two proportions are same.

Table 2 describes the close set identification used for the proposed method and the usual PCA method. The 'head' folder is used here. Both tables show that the threshold based-PCA outperforms the PCA method and higher the number of frames used for PCA projection, higher the recognition rate achieved. The experiment is carried out in Frequency domain.

#### 4.4 Open Test Identification in Face Space

For Open test identification two separate face class sets are used to verify the utility of the method formulated in Section 3. For any frame in the test set, one needs to decide whether person in that frame belongs to the training set or outside it. Identification rate is defined as

(the number of correct decisions) \* 100/ (number of frames in the test set).

It is apparent from Table 3 that in case of NN classifier the faces not present in the training set will be wrongly identified. The proposed threshold based system in this context performs

**Table 3:** Open set identification results.

Training Dataset	Test Dataset	No. of training frames per class	Identification rate Using NN classifier	Identification rate Using Class specific thresholds
First 20 persons from Head folder	First 20 persons sa1 folder	10 (ordered)	0	98 %
Last 20 persons from Head folder	Last 20 persons sa1 folder	10 (unordered)	0	99 %
First 20 persons from sa1 folder	Last 20 persons Head folder	10 (ordered)	0	97 %
First 20 persons from sa1 folder	Last 20 persons from Head folder	10 (unordered)	0	98 %
First 20 persons from Head folder	Last 23 persons from Head folder	10 (ordered)	0	98 %
First 20 persons from Head folder	Last 23 persons from sa1 folder	10 (ordered)	0	97 %

more efficiently. The proposed method for any real life application proves its utility where the test set can be any thing (face or non face).

The Data division is shown clearly in Table 3. The ordered frames are the 10 consecutive frames chosen as training dataset. 10 frames with 25 frame gap are chosen as unordered set. Next 30 frames of each class are used as test phase. 60% of the total number eigenvectors with the highest eigenvalues are used for subspace projection.

## 5. Conclusions and Discussion

In this paper we emphasized on the video-to-video face verification because for the proposed method the temporal information can easily be added. And the use of this temporal information helps to calculate the threshold value using set estimation. The result shows that in each case the proposed threshold PCA method outperforms the traditional PCA and with less time complexity. In the system the magnitude spectra plays an important role in videos as the facial movements are inherent nature of video face sequences. As an extension of the whole process phase spectra can also be tested with the other dimensionality reduction techniques like PCA-LDA, kernel PCA. The VidTIMIT dataset is designed on the near field effects with only one person in on the scene and with same background. The far field experiments can be applied with face tracker. We have probably taken the lowest possible such value for the number of training points of each class for video training. It is expected that the results can improve if the size of the training set is larger. For future work, one can try the proposed method on other PCA based subspace methods like 2DPCA, KPCA, 2DLDA, KLDA, modular PCA. The proposed threshold selection mechanism can be developed for those schemes with suitable modifications. Probably, the proposed method can be extended to other color spaces as well. For finding the MST of n points using Kruskal’s method, the complexity is  $O(n^2 \log n)$ . The complexity of the classifier to be used (in our method it is the Nearest Neighbor classifier) is to be added to the complexity of MST calculation for obtaining the complexity of the complete classification system.



## References

- [1] W. Zhao, R. Chellappa, A. Rosenfeld, and J. Phillips, *Face recognition: A Literature Survey* Technical Report, CS-TR4167, Univ. of Maryland, 2000.
- [2] D. Maio and D. Maltoni, *Real-time Face Location on Gray-Scale Static Images* Pattern Recognition, vol. 33, no. 9, pp. 1525-1539, 2000.
- [3] R. S. Feris, T. E. Campos and R. M. Cesar J., *Detection and Tracking of Facial Features in Video Sequences* Lecture Notes in Artificial Intelligence, vol. 1793,, Springer-Verlag. , 2000.
- [4] B.Li and R.Chellappa, *A Generic Approach to Simultaneous Tracking and Verification in Video* IEEE Transaction on Image Processing 11: 530-544 , 2002.
- [5] S. Zhou, V.Krueger, and R. Chellappa *Probablistic Recognition of Human Faces From Video* Computer Vision and Image Understanding,91,7,214-245, 2003.
- [6] P. J. Phillips, P. Grother, R. J. Micheals, D. M. Blackburn, E. Tabassi, and J. M. Bone, *FRVT 2002: Evaluation Report*, [http://www.frvt.org/DLs/FRVT 2002 Evaluation Report.pdf](http://www.frvt.org/DLs/FRVT%2002%20Evaluation%20Report.pdf), 2003.
- [7] A. K. Jain, A. Ross, and S. Prabhakar *An Introduction to Biometric Recognition* IEEE Transactions on Circuits and Systems for Video Technology, 14(1) January, 2004.
- [8] D. M. Blackburn *Biometrics 101, version 3.1*. Federal Bureau of Investigation. March , 2004.
- [9] A. J. Mansfield and J. L. Wayman *Best Practices in Testing and Reporting Performance of Biometric Devices, Version 2.01*. Centre for Mathematics and Scientific Computing, National Physical Laboratory, Queens Road, Teddington, Middlesex, TW11 OLW , 2002.
- [10] R.Sebastiao, J.Silva, A.Padilha *Face Recognition From Spatially Morphed Video Sequences*. Proceedings of the International Conference on Image Analysis and Recognition pp.365-374, Springer LNCS Berlin , 2006.
- [11] C. A. Murthy *On Consistent Estimation Of Classes in in The Context of Cluster Analysis* Ph.D Thesis, Indian Statistical Institute, Calcutta India , 1988.
- [12] H.Edelsbrunner, D.G Kirkpatrickand, and R.Seidel *On the Shape of A Set of Points in A Plane* IEEE Trans. On Inform. Theory, vol. IT-29, .551-559 , 1983.
- [13] D. P. Mandal, C. A. Murthy and S. K. Pal *Determining the Shape of A Pattern Class From Sampled Points: Extension To RN* Int. J. of General Systems, vol. 26, no. 4, pp. 293-320, 1997., 1997.
- [14] D. P. Mandal and C. A. Murthy *Selection of alpha for alpha-hull in R2* Pattern Recognition, vol. 30, no. 10, pp. 1759-1767, 1997.
- [15] U.Grenander *Abstract Inference* John Wiley, New York , 1981.
- [16] R.Bhagabatula and M.Savvides *Eigen and Fisher face Fourier Spectra for Shift Invariant Pose Tolerant Face Recognition* Proceedings of international Conference on Advances in Patten Recognition,U.K., 2005.
- [17] C.Sanderson and K.K. Paliwal *Identity Verification Using Speech and Face* Information Digital Signal Processing 14(5):449-480, 2004.
- [18] M.Orozco-Alzate, and C.G Castellanos-Dominguez *Comparison of the Nearest Feature Classifiers for Face Recognition* Machine Vision and Applications,17(5), pp 279-285.,
- [19] T.M.Cover P.E.Hart *Nearest neighbor Pattern Classification* IEEE Trans. Inform. Theory IT13 (1): 21-27.