ISSN 2320 - 2602
Volume 2, No.12, December 2013
International Journal of Advances in Computer Science and Technology
Available Online at http://warse.org/pdfs/2013/ijacst022122013.pdf

RADON TRANSFORM AND SYMBOLIC LINEAR DISCRIMINANT ANALYSIS BASED 3D FACE RECOGNITION USING KNN AND SVM

P. S. Hiremath, Manjunatha Hiremath[1]
[1]Department of Computer Science,
Gulbarga University, Gulbarga, Karnataka, India
hiremathps53@yahoo.com, manju.gmtl@gmail.com

ABSTRACT

In spite of over two decades of intense research, illumination and pose invariance remain prohibitively challenging aspects of face recognition for most practical application. Many recent events, such as terrorist attacks, have exposed the serious weaknesses in most sophisticated security systems. Automatic face recognition has long been established as one of the most active research areas in computer vision. In spite of the large number of developed algorithms, real-world performance of state-of-the-art methods has been disappointing. Three dimensional (3D) human face recognition is emerging as a significant biometric technology. Research interest in 3D face recognition has increased during recent years due to the availability of improved 3D acquisition devices and processing algorithms. In this paper, we have proposed a novel method for three dimensional (3D) face recognition using Radon transform and Symbolic LDA based features of 3D face images. In this method, the Symbolic LDA based feature computation takes into account the face image variations to a larger extent and has the advantage of dimensionality reduction. The experimental results have yielded 99.60% recognition accuracy using SVM with reduced computational cost, which compares well with other state-of-the-art methods.

Key words : 3D face recognition, radon transform, symbolic LDA, KNN, SVM.

1. INTRODUCTION

Biometrics refers to the identification of humans by their characteristics or traits. Biometrics is used in computer science as a form of identification and access control. It is also used to identify individuals in groups that are under surveillance. Many different aspects of human physiology, chemistry or behaviour can be used for biometric authentication. The selection of a particular biometric for use in a specific application involves a weighting of several factors. A number of biometric traits have been developed and are used to authenticate the person's identity. The idea is to use the special characteristics of a person to identify him. By using special characteristics we mean the using the features such as face, iris, fingerprint, signature etc.

The method of identification based on biometric characteristics is preferred over traditional passwords and PIN based methods for various reasons such as: The person to be identified is required to be physically present at the time-of-identification. Identification based on biometric techniques obviates the need to remember a password or carry a token. A biometric system is essentially a pattern recognition system which makes a personal identification by determining the authenticity of a specific physiological or behavioural characteristic possessed by the user. A biometric system can be either an 'identification' system or a 'verification' (authentication) system.

Human face images are useful not only for person recognition, but for also revealing other attributes like gender, age, ethnicity, and emotional state of a person. Therefore, face is an important biometric identifier in the law enforcement and human computer interaction (HCI) communities. Detecting faces in a given image and recognizing persons based on their face images are classical object recognition problems that have received extensive attention in the computer vision literature. While humans are perceived to be good at recognizing familiar faces, the exact cognitive processes involved in this activity are not well understood. Therefore, training a machine to recognize faces as humans do is an arduous task. However, general methods used in object recognition such as appearance based, model based, and texture based approaches are also applicable to the specific problem of face detection and recognition.

The face is the frontal portion of the human head, extending from the forehead to the chin and includes the mouth, nose, cheeks, and eyes. Being the foremost part in one’s interactions with the outer world, the face houses most of the fundamental sensory organs necessary for perceiving the world around, namely, eyes for seeing, nose for smelling, mouth for tasting, and ears for hearing. The face is considered to be the most commonly used biometric trait by humans; we recognize each other and, in many cases, establish our identities based on faces. Hence, it has become a standard practice to incorporate face photographs in various tokens of authentication such as ID cards, passports, and driver’s licenses.

Face Recognition and verification have been at the top of the research agenda of the computer vision community for more than a decade. The scientific interest in this research topic has been motivated by several factors. The main attractor is the inherent challenge that the problem of face image processing, face detection and recognition. However, the impetus for better understanding of the issues raised by automatic face recognition is also fuelled by the immense commercial significance that robust and reliable face recognition technology would entail. Its applications are envisaged in physical and logical access control, security, man-machine interfaces and low bitrate communication.

To date, most of the research efforts, as well as commercial developments, have focused on two dimensional (2D) approaches. This focus on monocular imaging has partly been motivated by costs but to a certain extent also by the need to retrieve faces from existing 2D image and video database. With recent advances in image capture techniques and devices, various types of face-image data have been utilized and various algorithms have been developed for each type of image data. Among various types of face images, a 2D intensity image has been the most popular and common image data used for face recognition because it is easy to acquire and utilize. It, however, has the intrinsic problem that it is vulnerable to the change of illumination. Sometimes the change of illumination gives more difference than the change of people, which severely degrades the recognition performance. Therefore, illumination-controlled images are required to avoid such an undesirable situation when 2D intensity images are used. To overcome the limitation of 2D intensity images, Three Dimensional (3D) images are being used, such as 3D meshes and range images. A 3D mesh image is the best 2D representation of 3D objects. It contains 3D structural information of the surface as well as the intensity information of each point. By utilizing the 3D structural information, the problem of vulnerability to the change of illumination can be solved. A 3D mesh image is suitable image data for face recognition, but it is complex and difficult to handle.

A range image is simply an image with depth information. In other words, a range image is an array of numbers where the numbers quantify the distances from the focal plane of the sensor to the surfaces of objects within the field of view along rays emanating from a regularly spaced grid. Range images have some advantages over 2D intensity images and 3D mesh images. First, range images are robust to the change of illumination and colour because the value on each point represents the depth value which does not depend on illumination or colour. Also, range images are simple representations of 3D information. The 3D information in 3D mesh images is useful in face recognition, but it is difficult to handle. Different from 3D mesh images, it is easy to utilize the 3D information of range images because the 3D information of each point is explicit on a regularly spaced grid. Due to these advantages, range images are very promising in face recognition.

The majority of the 3D face recognition studies have focused on developing holistic statistical techniques based on the appearance of face range images or on techniques that employ 3D surface matching. A survey of literature on the research work focusing on various potential problems and challenges in the 3D face recognition can be found in the survey[1-5,16,17]. Gupta et al.[6] presented a novel anthropometric 3D face recognition algorithm. This approach employs 3D Euclidean and Geodesic distances between 10 automatically located anthropometric facial fiducial points and a linear discriminant classifier with 96.8% recognition rate. Lu et al.[7] constructed many 3D models as registered templates, then they matched 2.5D images (original 3D data) to these models using iterative closest point (ICP). Chang et al. [8] describe a “multi-region” approach to 3D face recognition. It is a type of classifier ensemble approach in which multiple overlapping sub regions around the nose are independently matched using ICP and the results of the 3D matching are fused. Jahanbim et al. [9] presented an approach of verification system based on Gabor features extracted from range images. In this approach, multiple landmarks (fiducials) on face are automatically detected, and also the Gabor features on all fiducials are concatenated, to form a feature vector to collect all the face features. Hiremath et al.[18] have discussed the 3D face recognition by using Radon Transform and PCA with recognition accuracy of 95.30%. Hengliand Tang et al.[19] presented a 3D face recognition algorithm based on sparse representation. In this method they used geo-metrical features, namely, triangle area, triangle normal and geodesic distance.

In this paper, our objective is to propose Radon transform and Symbolic LDA based 3D face recognition. The experimentation is carried out using three publicly available databases, namely, Bhosphorus, Texas and CASIA 3D face databases.

2. MATERIALS AND METHODS

For purpose of experimentation of the proposed methodology, the face images drawn from the following 3D face databases are considered: (i) Boshphorus 3D face database, (ii) Texas 3D face database, (iii) CASIA 3D face database.

2.1 Bosphorus 3D Face Database

The Bosphorus 3D face database consists of 105 subjects in various poses, expressions and occlusion conditions. The 18 subjects have beard/moustache and the 15 subjects have hair. The majority of the subjects are aged between 25 and 35. There are 60 men and 45 women in total, and most of the subjects are Caucasian. Two types of expressions have been considered in the Bosphorus database. In the first set, the expressions are based on action units. In the second set, facial expressions corresponding to certain emotional expressions are collected. These are: happiness, surprise, fear, sadness, anger and disgust.

The facial data are acquired using Inspeck Mega Capturor II 3D, which is a commercial structured-light based 3D digitizer device. The sensor resolution in x, y & z (depth) dimensions are 0.3mm, 0.3mm and 0.4mm respectively, and colour texture images are high resolution (1600x1200 pixels). It is able to capture a face in less than a second. Subjects were made to sit at a distance of about 1.5 meters away from the 3D digitizer. A 1000W halogen lamp was used in a dark room to obtain homogeneous lighting. However, due to the strong lighting of this lamp and the device's projector, usually specular reflections occur on the face. This does not only affect the texture image of the face but can also cause noise in the 3D data. To prevent it, a special powder which does not change the skin colour is applied to the subject's face. Moreover, during acquisition, each subject wore a band to keep his/her hair above the forehead to prevent hair occlusion, and also to simplify the face segmentation task. The propriety software of the scanner is used for acquisition and 3D model reconstruction[10].

2.2 <u>Texas 3D Face Database</u>

The Texas 3D Face Recognition (Texas 3DFR) database is a collection of 1149 pairs of facial color and range images of 105 adult human subjects. These images were acquired using a stereo imaging system manufactured by 3Q Technologies (Atlanta, GA) at a very high spatial resolution of 0.32 mm along the x, y, and z dimensions. During each acquisition, the color and range images were captured simultaneously and thus the two are perfectly registered to each other. This large database of two 2D and 3D facial models was acquired at the company Advanced Digital Imaging Research (ADIR), LLC (Friendswood, TX), formerly a subsidiary of Iris International, Inc. (Chatsworth, CA), with assistance from research students and faculty from the Laboratory for Image and Video Engineering (LIVE) at The University of Texas at Austin. This project was sponsored by the Advanced Technology Program of the National Institute of Standards and Technology (NIST). Texas 3DFRD was created to develop and test 3D face recognition algorithms intended to operate in environments with cooperative subjects, wherein, the faces are imaged in a relatively fixed position and distance from the camera [11].

2.3 <u>CASIA 3D Face Database</u>

CASIA 3D Face Database consisting of 4624 scans of 123 persons using the non-contact 3D digitizer, Minolta Vivid 910. During building the database, not only the single variations of poses, but also expressions and illuminations are considered [12].

3. PROPOSED METHOD

The proposed methodology employs the following:
(i) Radon transform(RT) and
(ii) Symbolic Linear Discriminant Analysis (Symbolic LDA), which are described in the following sections.

3.1 <u>Radon Transform</u>

The radon transform (RT) is a fundamental tool in many areas. The 3D radon transform is defined using 1D projections of a 3D object *f(x,y,z)* where these projections are obtained by integrating *f(x,y,z)* on a plane, whose orientation can be described by a unit vector $\vec{\alpha}$. Geometrically, the continous 3D radon transform maps a function $\mathbb{R}^3$ into the set of its plane integrals in $\mathbb{R}^3$. Given a 3D function $f(\vec{x}) \cong f(x,y,z)$ and a plane whose representation is given using the normal $\vec{\alpha}$ and the distance s of the plane from the origin, the 3D continuous radon transform of f for this plane is defined by

$$\Re f(\vec{\alpha}, s) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(\vec{x})\delta(\vec{x}^T\alpha - s)d\vec{x}$$

$$= \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(x,y,z)\delta(x\sin\theta\cos\phi + y\sin\theta\sin\phi + z\cos\theta - s)dxdydz$$

where $\vec{x} = [x,y,z]^T$,
$\vec{\alpha} = [\sin\theta\cos\phi, \sin\theta\sin\phi, \cos\theta]^T$, and δ is Dirac's delta function defined by $\delta(x) = 0, x \neq 0, \int_{-\infty}^{\infty}\delta(x)dx = 1$.

The radon transform maps the spatial domain (x,y,z) to the domain $(\vec{\alpha}, s)$ [13].

3.2 <u>Symbolic Faces</u>

Consider the 3D range face images $\Gamma_1, \Gamma_2, \ldots \Gamma_n$, each of size $N \times M$, from a 3D face image database. Let $\Omega = \{\Gamma_1, \Gamma_2, \ldots \Gamma_n\}$ be the collection of n face images of the database, which are first order objects. Each object $\Gamma_l \in \Omega$, $l = 1, 2, \ldots, n$, is described by a feature vector $(\tilde{Y}_1, \ldots, \tilde{Y}_p)$, of length p=NM, where each component $\tilde{Y}_j$, $j = 1, 2, \ldots, p$, is a single valued variable representing the range values of the 3D face image Γ_l. An image set is a collection of 3D range face images of m different subjects; each subject has same number of images but with different facial expressions and illuminations. There are m number of second order objects (face classes) denoted by $c_1, c_2, \ldots, c_m$, each consisting of different individual images $\Gamma_l \in \Omega$. We denote the set $E = \{c_1, c_2, \ldots, c_m\}$ and $c_i \subseteq \Omega$, $i = 1, 2, \ldots, m$. The feature vector of each face class $c_i \in E$ is described by a vector of p interval variables $Y_1, Y_2, \ldots, Y_p$, and is of length $p = NM$. The interval variable Y_j of face class c_i is declared by $Y_j(c_i) = [\underline{x}_{ij}, \overline{x}_{ij}]$, where $\underline{x}_{ij}$ and $\overline{x}_{ij}$ are minimum and maximum intensity values, respectively, among j^{th} range values of all the images of face class c_i. This interval incorporates information of the variability of j^{th} feature inside the i^{th} face class. We denote $X(c_i) = (Y_l(c_i), ..., (Y_p(c_i))$. The vector $X(c_i)$ of symbolic variables is recorded for each $c_i \in E$, and can be described by a symbolic data vector which is called as symbolic face[14-17] : $X(c_i) = (a_{i1}, a_{i2}, ..., a_{ip})$, where $aij = Y_j(c_i)$, $j = 1, 2, ..., p$ We represent the m symbolic faces by a $m \times p$ matrix :

$$\underline{X} = \begin{pmatrix} a_{11} & ... & a_{1p} \\ . & . & . \\ a_{m1} & ... & a_{mp} \end{pmatrix} = (a_{ij})_{m \times p}$$

3.3 Symbolic LDA

We consider the extension of linear discriminant analysis (LDA) to symbolic data analysis frame work [14-17]. Consider the 3D range face images $\Gamma_1, \Gamma_2, ..., \Gamma_n$, each of size M x N, from Texas 3D range face image database. Let $\Omega = \Gamma_1, \Gamma_2, ..., \Gamma_n$ be the collection of n 3D range face images of the database, which are first order objects. Each object $\Gamma_l \in \Omega$, $l = 1, 2, ..., n$, is described by a matrix A_l $(l = 1, 2, ..., n)$, where each component $\tilde{Y}_{ab}, a = 1, 2, ..., M$, and b=1,2,…,N, is a single valued variable representing the 3D range values of the face image Γ_l. An image set is a collection of face images of m different subjects and each subject has different images with varying expressions and illuminations. Thus, there are m number of second order objects (face classes) denoted by $E = \{c_1, c_2, ..., c_m\}$, each consisting of different individual images, $\Gamma_l \in \Omega$, of a subject. The face images of each face class are arranged from right side view to left side view. The feature matrix of k^{th} sub face class c_i^k of i^{th} face class c_i, where $k = 1, 2, ..., q$, $i = 1, 2, ..., m$, is described by a matrix X_i^k of size $M \times N$ that contains interval variable a_{iab}^k, $a = 1, 2, ..., M$, and $b = 1, 2, ..., N$. The matrix is called as symbolic face and is represented as :

$$X_i^k = \begin{bmatrix} a_{i11}^k & ... & a_{i1N}^k \\ . & . & . \\ a_{iM1}^k & .... & a_{iMN}^k \end{bmatrix}$$

The interval variable a_{iab}^k of k^{th} sub face class c_i^k of i^{th} face class c_i is described as $a_{iab}^k(c_i^k) = [\underline{x}_{iab}^k, \overline{x}_{iab}^k]$, where $\underline{x}_{iab}^k$ and $\overline{x}_{iab}^k$ are minimum and maximum intensity values, respectively, among $(a,b)^{th}$ feature inside the k^{th} sub face class of i^{th} face class. Thus, we obtain the qm symbolic faces from the given image database.

Now, we apply LDA method to the centers $x_{iab}^k \in$ ¡ of the interval $[\underline{x}_{iab}^k, \overline{x}_{iab}^k]$ given by

$$x_{iab}^{k^c} = \frac{\overline{x}_{iab}^k + \underline{x}_{iab}^k}{2}$$

The $M \times N$ symbolic face $X_i^{k^c}$ containing the centers $x_{iab}^{k^c} \in R$ of the intervals a_{iab}^k of symbolic face X_i^k is given by

$$X_i^{k^c} = \begin{bmatrix} a_{i11}^{k^c} & ... & a_{i1N}^{k^c} \\ . & . & . \\ a_{iM1}^{k^c} & .... & a_{iMN}^{k^c} \end{bmatrix}$$

In the symbolic LDA approach, to calculate the scatter (within and between class) matrices of qm symbolic faces X_i^k , where i=1,2,…,m and k=1,2,…,q, we define the within-class image scatter matrix S_w as

$$S_w = \sum_{i=1}^{m} \sum_{k=1}^{q} (X_i^{k^c} - M_i)^T (X_i^{k^c} - M_i)$$

where $M_i = \frac{1}{q} \sum_{k=1}^{q} X_i^{k^c}$, and the between-class image scatter matrix S_b as

$$S_b = \sum_{i=1}^{m} (M_i - M)^T (M_i - M),$$

where $M = \frac{1}{qm} \sum_{i,k} X_i^{k^c}$. In discriminant analysis, we want to determine the projection axis that maximizes the ratio $\frac{\det\{S_b\}}{\det\{S_w\}}$. In other words, we want to maximize the between-class image scatter matrix while minimizing the within-class image scatter matrix. It has been proved [10,14] that this ratio is maximized when the column vector of projection axis V is the eigenvector of $S_w^{-1} S_b$ corresponding to first p largest eigenvalues. For each symbolic face X_i^k , the family of projected feature vectors, $Z_1, Z_2, ..., Z_p$ are considered as:

$$Z_s = X_i^k V_s$$

where s=1,2,…,p. Let $B_i^k = [Z_1, Z_2, ..., Z_p]$, which is called as the feature matrix of the symbolic face X_i^k. The feature matrix B_{test} of the test image X_{test} is obtained as :

$$Z_{(test)s} = X_{test} V_s \ ,$$

where s=1,2,…,p and $B_{test} = [Z_{(test)1}, Z_{(test)2}, ..., Z_{(test)p}]$.

3.4 Proposed Method

The Figure 1 shows the overview of proposed framework. The algorithms of the training phase and the testing phase of the proposed method are given below:

Algorithm 1: Training Phase

1. Input the range image I_1 from the training set containing M images.
2. Apply Radon transform, from 0^o to 180^o orientations (in steps of *h*), to the input range image I_1 yielding a binary image I_2.
3. Superpose the binary image I_2 obtained in the Step 2 on the input range image I_1 to obtain the cropped facial range image I_3.
4. Repeat the Steps 1 to 3 for all the M facial range images in the training set.
5. Apply Symbolic LDA to the set of cropped facial range.
6. Compute the weights w_1 , w_2 , ..., w_p for each training face image, where p < M is the dimension of eigen subspace on which the training face image is projected.
7. Store the weights w_1 , w_2 ,..., w_p for each training image as its facial features in the Symbolic LDA feature library of the face database.

Algorithm 2: Testing Phase

1. Input the test range image Z_1.
2. Apply Radon transform, from 0^o to 180^o orientations (in steps of h), to the input range image Z_1 yielding a binary image Z_2.
3. Superimpose the binary image Z_2 on Z_1 to obtain the cropped facial image Z_3.
4. Compute the symbolic weights $w_i^{test}, i = 1, 2, ..., p$, for the test image Z_1 by projecting the test image on the Symbolic LDA feature subspace of dimension *p*.
5. Compute the Euclidian distance D between the feature vector w_i^{test} and the feature vectors stored in the Symbolic LDA feature library.
6. The face image in the face database, corresponding to the minimum distance D computed in the Step 5, is the recognized face.
7. Output the texture face image corresponding to the recognized facial range image of the Step 6.

4. RESULTS AND DISCUSSION

The proposed method is implemented using Intel Core 2 Quad processor @ 2.66 GHz machine and MATLAB 7.9. In the training phase, 10 frontal face images, with different expressions, of each of the 100 subjects are selected as training data set. For each face class (subject), two subclasses are formed; one subclass contains the face images with varying illumination, while the other subclass contains the face images of the same subject with varying facial expressions. In the testing phase, randomly chosen 200 face images of the Texas 3D face database with variations in facial expressions are used. The sample training images which are used for our experimentation are shown in the Figure 2, and their corresponding texture images are shown in the Figure 3. The performance comparison of the proposed method with the RT+PCA, RT+PCA+LDA and RT+ Symbolic PCA[18], in terms of recognition accuracy is presented in the Table 1. The graph of recognition rates versus the number of eigenfaces is shown in the Figure 4 for the proposed method (RT+Symbolic LDA). It is observed that the recognition rate improves as the number of eigenfaces is increased. It is 99.60% for 5 LDA components using SVM classifier in case of the proposed method. Further, the proposed method based on RT and Symbolic LDA outperforms the PCA, RT+PCA, RT+PCA+LDA and RT+Symbolic PCA [18] methods. The Figure 5 shows the receiver operating characteristic (ROC) curve for the proposed method, where x-axis and y-axis denote FAR and FRR, for Bhosphorus, Texas and CASIA 3D face databases with equal error rate 13.3436, 11.3529 and 10.0113 respectively.

5. CONCLUSION

In this paper, we have proposed a novel method for three dimensional (3D) face recognition using Radon transform and Symbolic LDA based features of 3D range face images. In this method, the Symbolic LDA based feature computation takes into account face image variations to a larger extent and has advantage of dimensionality reduction. The experimental results have yielded 99.60% recognition accuracy using SVM classifier with reduced complexity and a small number of features, which compares well with other state-of-the-art methods. The experimental results demonstrate the efficacy and the robustness of the method to illumination and pose variations. The recognition accuracy can be further improved by considering a larger training set and a better classifier.

ACKNOWLEDGEMENT

The authors are grateful to the referees for their helpful comments and suggestions. Also, the authors are indebted to the University Grants Commission, New Delhi, for the financial support for this research work under UGC-MRP F.No.39-124/2010 (SR)

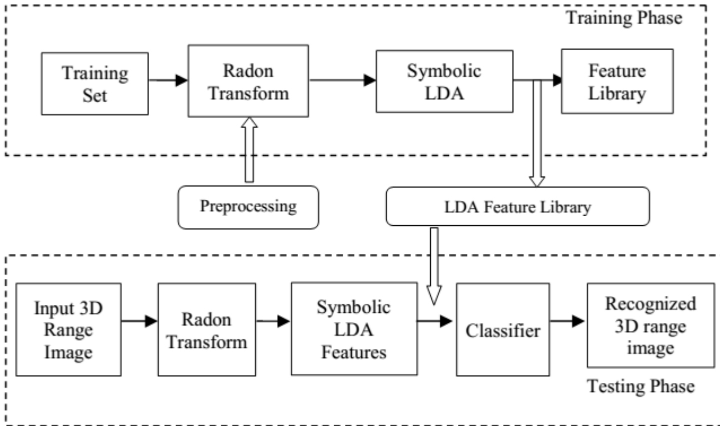
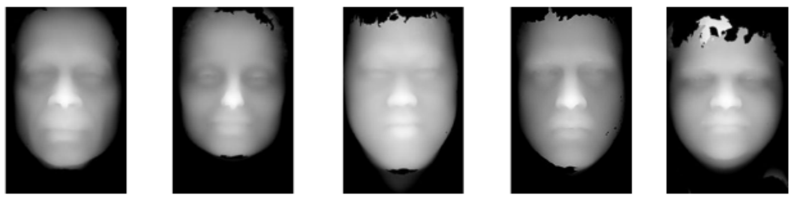


Figure 1. Overview of the proposed framework



(a) (b) (c) (d) (e)

Figure 2. Sample range images of the training set.

(a) (b) (c) (d) (e)

Figure 3. The facial texture images corresponding to the training range images of the Figure 2

Table 1. Performance comparison of the proposed with the RT+PCA, RT+PCA+LDA and RT+ Symbolic PCA, in terms of recognition accuracy.

No. of Eigenfaces	Recognition Accuracy (in %)						Average Time Taken For Recognition (in Secs.)
	RT+PCA [18]	RT + Symbolic PCA[21]	RT + PCA + LDA[18]	RT+Symbolic LDA (Proposed Method)			
				Minimum Distance Classifier	KNN (K=5)	SVM	
5	60.10	62.00	61.60	63.46	63.96	64.46	9.265
10	77.50	78.00	77.90	80.06	80.46	81.46	9.292
15	84.36	85.50	85.10	87.46	87.76	87.96	9.405
20	90.19	91.00	91.20	93.46	93.96	93.96	9.421
25	94.10	95.00	94.20	96.56	96.96	97.16	9.727
30	94.16	96.00	95.91	97.46	98.46	98.96	10.166
35	95.20	96.50	97.90	98.46	98.46	99.26	10.216
40	95.30	97.00	99.16	99.50	99.56	**99.60**	11.105

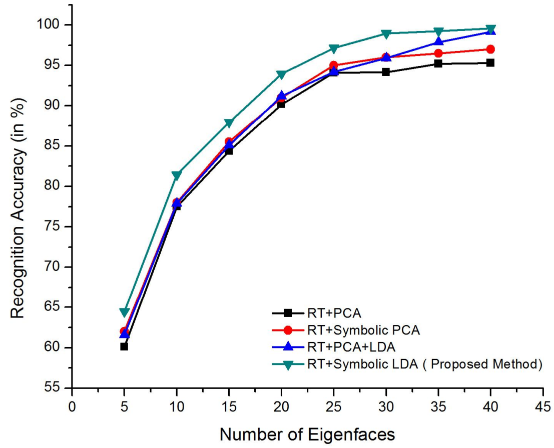


Figure 4. The graph showing Performance comparison of the proposed with the RT+PCA, RT+PCA+LDA and RT+ Symbolic PCA, in terms of recognition accuracy

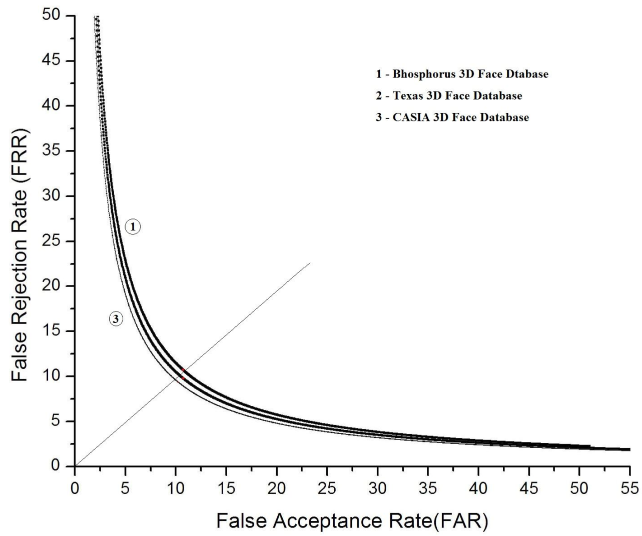


Figure 5. Receiver operating characteristic (ROC) curve for the proposed method, where x-axis and y-axis denote FAR and FRR, for Bhosphorus, Texas and CASIA 3D face databases with equal error rate 13.3436, 11.3529 and 10.0113 respectively.

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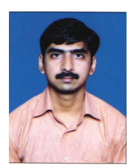
Dr. P. S. Hiremath was born in May 1952, and has obtained Ph.D. (1978) in Applied Mathematics and M.Sc. (1973) in

Applied Mathematics, from Karnataka University, Dharwad, Karnataka, India. He had been in the Faculty of Mathematics and Computer Science of various institutions in India, namely, National Institute of Technology, Surathkal (1977-79), Coimbatore Institute of Technology, Coimbatore (1979-80), National Institute of Technology, Tiruchirapalli (1980-86), Karnataka University, Dharwad (1986-1993) and has been presently working as Professor of Computer Science in Gulbarga University, Gulbarga (1993 onwards). His research areas of interest are Computational Fluid Dynamics, Optimization Techniques, Image Processing and Pattern Recognition, and Computer Networks. He has published 156 research papers in peer reviewed International Journals and Proceedings of International Conferences.

Manjunatha Hiremath was born in July 1984, and has obtained M.Phil (2010) in Computer Science and M.Sc.



(2008) in Computer Science from Gulbarga University, Gulbarga. Presently, he is working as Project Fellow in UGC Major Research Project since February 2011. His area of research interest is Image Processing and Pattern Recognition. He has published 8 research papers in peer reviewed International Journals and Proceedings of International Conferences.

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