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3D Face Recognition Using Radon Transform and Factorial Discriminant Analysis (FDA)

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Abstract— Automatic recognition of human faces is considered to be a challenging task despite significant progress in both computer vision and pattern recognition. A facial recognition system is a computer application of automatically identifying or verifying a person from a digital image or a video frame from a video source. Typical variations such as in-depth pose changes or illumination variations increase the dissimilarity of two face images of the same person more than the dissimilarity of different persons' face images. In this paper, we have proposed a novel method for three dimensional (3D) face recognition using Radon transform and Factorial Discriminant Analysis. In this method, the Factorial Discriminant Analysis (FDA) based feature computation takes into account of face image variations to a larger extent and has the advantage of dimensionality reduction. The experimental results have yielded 99.66% recognition performance with reduced computational cost, which compares well with other state-of-the-art methods in the literature.

Keywords— 3D face recognition, range image, radon transform, factorial discriminant analysis(FDA).

I. INTRODUCTION

A facial recognition system is a computer application for automatically identifying or verifying a person using a digital image or a video frame from a video source. One of the ways to do this is by comparing selected facial features from the image and a facial database. Two dimensional face recognition systems rely on the intensity values of images to extract significant features of the face in an image and have been an active research area for more than three decades. One of the most influential 2D face recognition algorithms is the Eigenface approach by Turk and Pentland[11]. Today, mature 2D face recognition systems are available that achieve low error rates in controlled environments. However, face recognition based on 2D images is still quite sensitive to illumination, pose variation, make-up and facial expressions. Moreover, a facial photo is easy to acquire even without consent of an individual and may be used to spoof a 2D face recognition system. A newly emerging trend, claimed to achieve improved accuracies, is three-dimensional face recognition. This technique uses 3D sensors to capture information about the shape of a face. This information is then used to identify distinctive features on the surface of a face, such as the contour of the eye sockets, nose, and chin. In contrast to 2D face recognition, 3D face recognition relies on the geometry of the face, not only on texture information. Due to this fundamentally different approach, it has the potential to overcome the shortcomings of 2D approaches. One advantage of 3D facial recognition is that it is not affected by changes in lighting like other techniques. It can also identify a face from a range of viewing angles, including a profile view. Three-dimensional data points from a face vastly improve the precision of facial recognition. The 3D research is enhanced by the development of sophisticated sensors that do a better job of capturing 3D face imagery. The sensors work by projecting structured light onto the face. Up to a dozen or more of these image sensors can be placed on the same CMOS chip—each sensor captures a different part of the spectrum. Modeling and faking the geometry of a face is much more expensive than the 2D fake scenario.

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 [1-9]. The most prominent method in current 3D face recognition system is to use 3D point clouds to represent faces. In point cloud-based approaches, raw 3D point sets are used to register faces, and then features are extracted from registered faces[10]. Many recognition systems use depth or range images, where each pixel value represents the distance from the sensor to the facial surface. The 3D face recognition is then formulated as a problem of dimensionality reduction for planar images. The principal component analysis (PCA) based "Eigenfaces" can be used for dimensionality reduction [11]. The basis vectors are however typically holistic and of global support. The PCA can be combined with the linear discriminant analysis (LDA) to form "Fisherfaces" with enhanced class seperability properties [12,13]. Hiremath and Manjunath H. [28] have employed radon transform, PCA and LDA data analysis approach for 3D face recognition, which is further extended to symbolic data analysis framework [30] yielding recognition accuracy of 95.30% and 99.50%, respectively. In this paper, the objective is to propose a new 3D face recognition method based on radon transform and factorial discriminant analysis, which are applied on 3D facial range images. The experimentation is done using three publicly available databases, namely, Texas 3D face database, Bhosphorus 3D face database and CASIA 3D face database. The experimental results demonstrate the effectiveness of the proposed method.

II. MATERIALS AND METHODS

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

A. Texas 3D Face Database :

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 co-operative subjects, wherein, the faces are imaged in a relatively fixed position and distance from the camera[16-18].

B. 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[19].

C. CASIA 3D Face Database :

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 [20].

III. PROPOSED METHODOLOGY

The proposed methodology employs the following: (i) Radon transform(RT) and (ii) Factorial Discriminant Analysis (FDA), which are describes in the following sections.

A. Radon Transform:

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 $f(\vec{x}) \equiv f(x,y,z)$ 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

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

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

where $\vec{x} = [x,y,z]^T$, $\vec{\alpha} = [\sin\theta\cos\phi, \sin\theta\sin\phi, \cos\theta]^{\mathrm{T}}$, 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 ($\vec{\alpha}, s$) are not the polar coordinates of (*x,y,z*). The 3D continuous Radon Transform satisfies the 3D Fourier slice theorem [14,15].

B. **Factorial Discriminant Analysis (FDA):**

Factorial Discriminant Analysis (FDA) is performed on a 3D face data set $E = \{1,...,n\}$ on n individuals (training set) which are each characterized by a vector of p quantitative predictor variables $Y = (Y_1, Y_2, ..., Y_p)'$. Each element k of E belongs to one of m classes $\Pi_1, \Pi_2, ..., \Pi_m$, and their membership is known a priori. It is described by a nominal variable c on E with m categories: $c(k) = i$ if k belongs to Π_i [21].

FDA deals with two aims: a descriptive one that consists in finding p' new discriminant variables, also called canonical variables (with $p' \leq p$), as linear combinations of the p predictors, such that the projections of the m classes are well separated in the space of canonical variables. The second objective of FDA is the decision-oriented one, which deals with the specification of a classification rule (both geometrical or probabilistic) in order to assign new individuals, for which the same variables $Y_j \,(j = 1,..., p)$ have been observed to one of the given classes $\Pi_i \,(i = 1,...,m)$.

FDA starts from a classical data matrix $X = (x_{kj})_{n\times p}$ with $x_{kj} = Y_j(k)$, where the j^{th} column corresponds to the j^{th} explicative variable Y_j. Let $C = (c_{ki})$ denote the $n \times m$ indicator matrix associated to the classificatory variable c such that $c_{ki} = 1 (or\, 0)$ iff $c(k) = i$ (or not), i.e., if the k^{th} individual belongs to the class Π_i (or not). The discriminant variables to be constructed should maximize the variance between the classes (in the training set E) and, at the same time, minimize the variance within the classes. Assuming X to be a centered matrix, the global empirical covariance matrix V of the data matrix X is given by

$$V = \left(\frac{1}{n} \sum_{k=1}^{n} x_{kj} x'_{kl} \right)_{p\times p} = X'HX$$

where H is the matrix of the weights of the individuals. Supposing all weights to be equal to $1/n$, we get $H = n^{-1} I_n$ (with I_n the identity matrix of dimension $n \times n$). Suppose that C_i is the sub-set of elements k of E (i.e., $C \subset E$), which belong to the class Π_i, and $n_i = |C_i|$ is the number of these elements. If the diagonal matrix Q of the weights n_i/n of the classes is denoted by

$$Q := diag\left(\frac{n_1}{n}, ..., \frac{n_m}{n} \right) = C'HC,$$

the centroids $\bar{x}_{C_i}$ of the m classes C_i given by:

$$\bar{x}_{C_i} = n_i^{-1} \sum_{k \in C_i} x_{kj}, \quad \text{for } i = 1,...,m,$$

are just the rows of the matrix: $\tilde{G} := \begin{pmatrix} \bar{x}'_{C_1} \\ . \\ . \\ . \\ \bar{x}'_{C_m} \end{pmatrix} = Q^{-1}(C'HX)$.

With this notation, the $p \times p$ covariance matrix B between the classes $C_1, ..., C_m$ is given by :

$$B = \sum_{i=1}^{m} \frac{n_i}{n} \bar{x}_{C_i} \bar{x}_{C_i}' = (X'HC) Q^{-1} (C'HX)$$

The *between-class* variance of the data vectors $x_1, ..., x_n$ is equal to $tr(B)$. Factorial discriminant analysis assumes that the underlying variance-covariance matrices in the m classes Π_i are all the same and therefore considers, as its estimate, the empirical variance-covariance matrix W within the classes $C_1, ..., C_m$ is

$$W := n^{-1} \sum_{i=1}^{m} n_i . W_i$$

which is obtained as a weighted sum of the empirical variance-covariance matrices W_i of the classes C_i given by:

$$W_i = (n_i)^{-1} \sum_{x_k \in C_i} (x_k - \overline{x}_{C_i})(x_k - \overline{x}_{C_i})'$$

$tr(W)$ is the *within-class* variance of the data vectors of E.

The first step of a discriminant analysis is to look for a 'discriminant axis' $\eta \in \mathbb{R}^p$ such that the m groups $C_1,...,C_m$ are distinguished as well as possible in the sense as to maximize the ratio of the *between* and *within* variances of the observed elements of the training set. Due to $V = W + B$, this solve the maximization problem:

$$\max_{\eta \in \mathbb{R}^p} \frac{\eta' B \eta}{\eta' V \eta}$$

The optimum η_1 is obtained as solution of the eigen-equation:

$$B\eta = \lambda V \eta \quad or \quad V^{-1} B \eta = \lambda \eta$$

corresponding to the largest eigenvalue λ_1 of the matrix $V^{-1}B$, which represents a measure of the discriminating power of the first factorial axis η_1. The other factorial axes are obtained as the eigenvectors $\eta_2, \eta_3, ...$ associated to the next largest eigenvalues $\lambda_2 \geq \lambda_3 \geq ...$ of the matrix $V^{-1}B$ in decreasing order.

In the s-dimensional factorial plane, the α^{th} coordinate of the individual $k \in E$ is given by the k^{th} element of the discriminant variable $Z_\alpha = X\eta_\alpha$, for $\alpha = 1,...,s$; here s is the number of axes of the best discriminant subspace. Similarly, the projection of the centroids $\overline{x}_{C_i}$ on the factorial plane has, as its α^{th} coordinate, the i^{th} element of the vector $(C'HC)^{-1}C'HZ_\alpha$.

C. **Proposed Method :**

The proposed methodology comprises the following steps:

(i) Radon transform is applied to the input depth and intensity images of a 3D face, which yields binary images that are used to crop the facial areas in the corresponding images.

(ii) Factorial discriminant analysis is applied to the cropped facial images, to achieve dimensionality reduction and obtain subsampled feature vectors.

(iii) Lastly, the minimum distance classifier is used to perform face recognition based on subsampled feature vectors.

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:

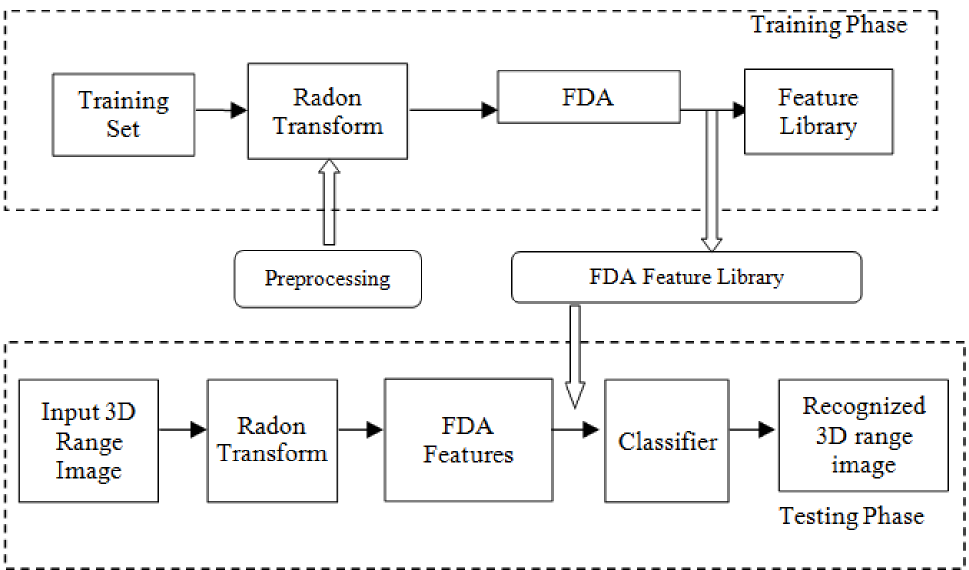

Figure 1. Overview of proposed framework

The algorithms of the training phase and the testing phase of the proposed method are given below:

Algorithm 1: Training Phase

1. Input the 3D face image I_1 from the training set containing 3D face data set $E = \{1, 2, ..., n\}$ of n individuals (training set) which are each characterized by a vector of p quantitative predicator variables $Y = (Y_1, Y_2, ..., Y_n)$. Each element k of E belongs to one of m classes $\Pi_1, \Pi_2, ..., \Pi_m$.
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 including subclasses in the training set.
5. Apply PCA to the set of cropped facial range images obtained in the Step 4 and obtain eigenfaces.
6. Compute the weights $w_1, w_2, ..., w_m$ for each training face image, where m < M is the dimension of feature subspace on which the training face image is projected.
7. After computing the weights perform FDA on feature subspace.
8. Store the weights $w_1, w_2, ..., w_m$ for each training image as its facial features in the feature library of the face database.

Algorithm 2: Testing Phase

1. Input the 3D face range test 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 weights $w_i^{test}, i = 1, 2, ..., m$, for the test image Z_1 by projecting the test image on the feature subspace of dimension m.
5. After computing the weights perform FDA on feature subspace.
6. Compute the Euclidian distance D between the feature vector w_i^{test} and the feature vectors w_i stored in the feature library.
7. The face image in the face database corresponding to the minimum distance D computed in the Step 6 is the recognized face. Output the texture face image corresponding to the recognized facial range image.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

As in typical biometric systems, the proposed method includes two phases: the training phase and the testing phase as illustrated in the Figure 1. The proposed method is implemented using Intel Core 2 Quad processor @ 2.66 GHz machine and MATLAB 2012b. The 4000 images of three databases, namely, Bhosphorus 3D face database, CASIA 3D face database and Texas 3D face database, that are divided into two subsets, which are the training set, and probe set. The training set has 300 subjects (classes) with three subsets of each subject and each subset contains 3 face images. The other 1300 images are randomly chosen as probe set (testing set) from all the three databases. The sample training set of 3D face images used for experimentation are shown in the Figure 2. The sample testing set of 3D face images used for experimentation are shown in the Figure 3.

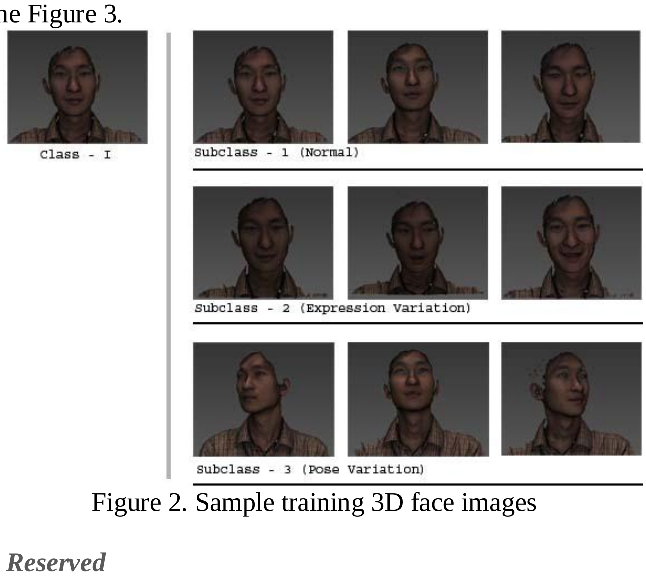

Figure 2. Sample training 3D face images

Figure 3. Sample testing 3D face images

The Table 1 shows performance comparison of the RT+Symbolic PCA, RT+PCA+LDA, RT+Symbolic LDA methods and proposed method in terms of recognition rates and the Table 2, shows the performance comparison of the proposed method with other methods. The Figure 4 shows a Receiver operating curve (ROC) space, which is defined by FAR versus FRR as x and y axes respectively, which depicts relative trade-offs between true positive and false positive for the FDA based face recognition for 3 databases, namely, Bhosphorus 3D face database, Texas 3D face database and CASIA 3D face database, with equal error rates (ERR) 9.9486, 9.0191and 8.6067 respectively. The reason for lower ERR for CASIA 3D database is due to the fact that it contains more sample images with variations in pose, expression and illumination as compared to the other two databases, which is responsible for better training in case of CASIA 3D face database.

Table -1. Performance comparison of RT+Symbolic PCA, RT+PCA+LDA, RT+Symbolic LDA and proposed method in terms of recognition rates

No. of Eigen Components	**RT + Symbolic PCA[25]**	**RT+PCA +LDA [28]**	**RT+ Symbolic LDA [30]**	**RT+FDA Proposed Method**
5	62.00%	61.60%	68.00%	69.00%
10	78.00%	77.90%	83.50%	85.00%
15	85.50%	85.10%	88.00%	91.20%
20	91.00%	91.20%	94.00%	95.00%
25	95.00%	94.20%	97.00%	97.00%
30	96.00%	95.91%	98.00%	98.50%
35	96.50%	97.90%	98.00%	98.50%
40	97.00%	99.16%	99.50%	**99.66%**

Table 2. The performance comparison of proposed method with other methods

Method	**Recognition Accuracy**
Faltemier et al. [23]	94.90%
Maurer et al. [24]	95.80%
Hiremath et al. [25]	97.00%
Kakadiaris et al. [26]	97.00%
H. usken et al. [27]	97.30%
Hiremath et al. [28]	99.16%
Mian et al.[29]	99.30%
Hiremath et al. [30]	99.50%
Proposed Method	**99.66%**

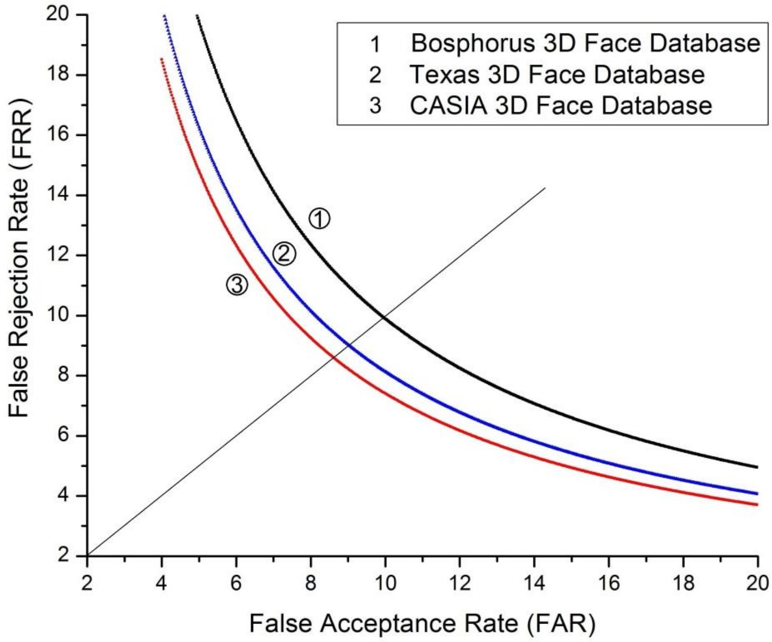

Figure. 4. Receiver operating characteristic (ROC) curve for the proposed method, where x-axis and y-axis denote FAR and FRR, for Bhosphorus, Texas and CASIA 3D face database with equal error rate 9.9486,9.0191and 8.6067 respectively.

V. Conclusion

In this paper, we have proposed a novel method for three dimensional (3D) face recognition using Radon transform and Factorial Discriminant Analysis (FDA) based features of 3D range face images. In this method, the FDA based feature computation takes into account of 3D face image variations to a larger extent and has advantage of dimensionality reduction. The experimental results have yielded 99.66% recognition performance 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.

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