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Symbolic Factorial Discriminant Analysis for 3D Face Recognition

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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. Often, 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 Symbolic Factorial Discriminant Analysis (Symbolic FDA) is proposed. In this method, the Symbolic Factorial Discriminant Analysis (Symbolic 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 99.80% recognition performance with reduced computational cost, which compares well with other state-of-the-art methods.

Index Term—3D face recognition, Range image, Radon transform, Symbolic factorial discriminant analysis (Symbolic FDA)

I. INTRODUCTION

A facial recognition system is a computer application for automatically identifying or verifying a person from a digital image or a video frame from a video source. Face recognition is one of the most active research issues in the field of pattern recognition and multimedia. The research significantly contributes to the improvement of computer intelligence. Over the past several decades, most work is being focused on 2D images. Due to the complexity of face recognition process, it is still hard to develop a robust automatic face recognition system. The difficulties mainly include the complex variations of poses, expressions, illumination and aging. According to the evaluation of commercially available and mature prototype face recognition systems provided by face recognition vendor tests (FRVT), the recognition performance under the unconstrained condition is not satisfactory.

In fact, a human face is characterized by not only 2D texture information but also 3D shape information. Face representation using 2D images results in the loss of some information. An alternative idea is to represent the face as a realistic 3D model, which contains not only texture and shape information, but also structural information for simulating facial expressions. With rapid developments in the technology of 3D acquisition equipment, face recognition based on 3D information is attracting more and more attention. In 3D face recognition, depth information and surface features are used to characterize an individual. This is a promising way to understand human facial features in 3D space and to improve the performance of current face recognition systems.

A survey of literature on the research work focusing on various potential problems and challenges in the 3D face recognition can be found in [1-7]. The main technological limitation of 3D face recognition methods is the acquisition of 3D images, which usually requires a range camera. This is also a reason why 3D face recognition methods have emerged significantly later (in the late 1980s) than 2D methods. Recently commercial solutions have implemented depth perception by projecting a grid onto the face and integrating video capture of it into a high resolution 3D model.

In this paper, the objective is to propose a new 3D face recognition method based on radon transform and symbolic 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

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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 [8-10].

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, namely, happiness, surprise, fear, sadness, anger and disgust, are collected.

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 [11-12].

C. CASIA 3D Face Database

The 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 [13].

III. PROPOSED METHODOLOGY

The proposed methodology employs the following: (i) Radon transform(RT) and (ii) Symbolic Factorial Discriminant Analysis (Symbolic FDA), which are described 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 ($\vec{\alpha}, s$) [14,15].

B. Symbolic Factorial Discriminant Analysis (Symbolic FDA)

Let $\Omega = \{\Gamma_1, ..., \Gamma_n\}$ be the collection of n 3D face images of the database. An image set is a collection of face images of m different subjects (face class) denoted by

$E = \{c_1, c_2, ..., c_m\}$. We have assumed that images belonging to a face class are arranged from right side view to leftside view. The view range of each face class is partitioned into q sub face class and each sub face class contains r number of images. The feature vector of k^{th} sub face class c_i^k of i^{th} face class c_i where $k = 1, 2, ..., q$, is described by a vector of p interval variables $Y_i, ..., Y_p$, and is of length $p = NM$. The interval variable Y_j of k^{th} sub face class c_i^k of i^{th} face class is described as $Y_j(c_i^k) = [\underline{x}_{ij}^k, \overline{x}_{ij}^k]$, where $\underline{x}_{ij}^k$ and $\overline{x}_{ij}^k$ are minimum and maximum depth values, respectively, among j^{th} depth values of all the images of sub face class c_i^k . The vector X_i^k of interval variables is recorded for k^{th} sub face class c_i^k of i^{th} face class. This vector is called as symbolic face. We denote : $X_i^k = (Y_1(c_i^k), ..., Y_p(c_i^k))$, where $i = 1, ..., m$, and $k = 1, ..., q$ and $j = 1, ..., p$.

The interval variables of symbolic faces are coded into numerical form by fuzzy coding system in order to preserve as much as possible the numerical information of the original variables after their categorization. For this purpose, an interval type variable is transformed based on a fuzzy approach using special piecewise polynomial functions asB-Spline. In order to attain a reasonably small number of categories for the coded variables, typically low degree polynomials are used. By a B-Spline of degree one, or a semi linear transformation, the domain of each variable is split into two intervals and a fuzzy coding is performed by three semi linear functions, e.g. The threshold knots are chosen as the minimum and maximum values assumed by the variable, and the middle knot might be average, the median, or the semi range value of the variable [16].

According to the B-Spline coding system, a symbolic face X_i^k is coded as a unique row in the matrix corresponding to the values assumed by the $B-Spline$ functions for the value for a $X_i^k : B_1(Y_j(X_i^k)), B_2(Y_j(X_i^k)), B_3(Y_j(X_i^k))$. Finally, a global coding matrix $S_{N\times K}$ is constructed by combining coded descriptors. It can be also considered as a partitioned matrix built by $S = [|S_1|...|S_j|...|S_p|]$. After coding of the variables in terms of fuzzy coding, we find a quantification of the coded variables using Non-Symmetrical Multiple Correspondence Analysis (NS-MCA). The optimal quantification of the K categories of the p descriptors is obtained as solution of the eigen equation:

$$\frac{1}{N}(G' S \Delta_x^{-1} X' G - \frac{n}{N} G' U G)\omega_\alpha = \mu_\alpha \omega_\alpha$$

where $G_{N\times qm}$ is the indicator matrix that identifies the different symbolic faces of the set E. After having transformed the categorical predictions into optimal numerical variables, we can perform a classical FDA in order to look for a suitable subspace with optimum separation and, at the same time, obtaining a minimum internal dispersion of the corresponding symbolic faces. We denote by $\tilde{S}$ matrix collecting the new variables $|\Phi_1|...|\Phi_\alpha|...|\Phi_s|$ of the set E. The factorial discriminant axes are solutions of the Eigen equation:

$$[(\tilde{S}' H\tilde{S})(\tilde{S}' HC)(C' HC)^{-1}(C' H\tilde{S})]y_\alpha = \lambda_\alpha y_\alpha$$

where the column vectors of $\tilde{S}$ are centered, and C is the indicator matrix that specifies the membership of each symbolic face to just one of the m classes c_i, here H is the diagonal matrix with diagonal elements equal to $\frac{d_i}{qm}(i = 1, ..., m)$, where d_i are the class sizes, λ_α and y_α are the a^{th} eigenvalue and eigenvector, respectively, of the matrix in brackets. The eigenvectors of symbolic factorial discriminant analysis method can be obtained as $: V_{qm} = E' Y_{qm}$, where $Y_{qm} = (y_q, ..., y_m)$ and V_{qm} is the $p\times qm$ matrix with corresponding eigenvectors $v_1, v_2, ..., v_{qm}$, as its columns. The α^{th} eigenvector of V is denoted by $V_a = (V_{a1}, ..., V_{ap})$. A subspace is extracted by selecting L number of eigenvectors, which contain maximum variance and are denoted by $V_1, V_2, ..., V_L$, corresponding to eigenvalues $\lambda_1, \lambda_2, ..., \lambda_L$. Since, the symbolic face X_i^k is located between the lower bound symbolic face $\underline{X}_i^k$ and upper bound symbolic face $\overline{X}_i^k$, it is possible to find α^{th} interval principal component $[\underline{B}_{i\alpha}^k, \overline{B}_{i\alpha}^k]$ of symbolic faces S_i^k defined by $\underline{B}_{i\alpha}^k = X_i^k V_\alpha$ and $\overline{B}_{i\alpha}^k = X_i^k V_\alpha$.

C. *Proposed Algorithm*

The proposed methodology comprises the following steps:

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

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

(iii) Lastly, 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:
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 Eigen faces.
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 Symbolic 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 Symbolic 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 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. Some sample images of training set of 3D face images used for experimentation are shown in the Figure 2. Some sample images of testing set of 3D face images used for experimentation are shown in the Figure 3.

The Table 1 shows performance comparison of the proposed method with RT+Symbolic PCA[17], RT+PCA+LDA[17], RT+ Symbolic LDA[18], RT+FDA[24] methods in terms of recognition rates and the Table 2, shows the performance comparison of the proposed method with other methods in the literature. 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 positives and false positives for the Symbolic FDA based face recognition for 3D face databases, namely, Bhosphorus 3D face database, Texas 3D face database and CASIA 3D face database, which yield equal error rates (ERR) 9.7914, 8.9264 and 8.5286 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.

V. CONCLUSION

In this paper, a novel method is proposed for three dimensional (3D) face recognition using Radon transform and Symbolic Factorial Discriminant Analysis (Symbolic FDA) based features of 3D range face images. In this method, the Symbolic 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 99.80% 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.

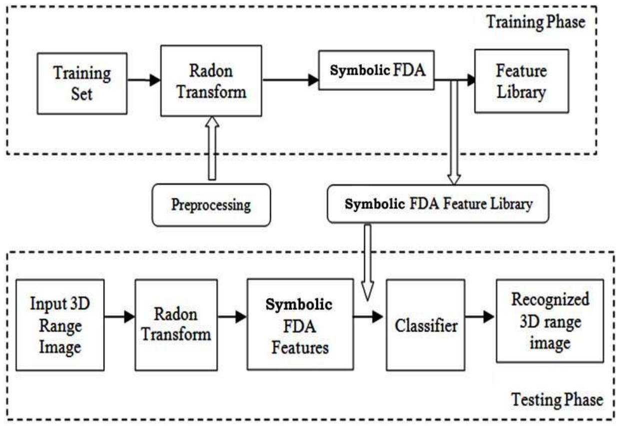

Figure 1. Overview of proposed framework

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Figure 2: Sample training 3D face images

Figure 3. Sample testing 3D face images

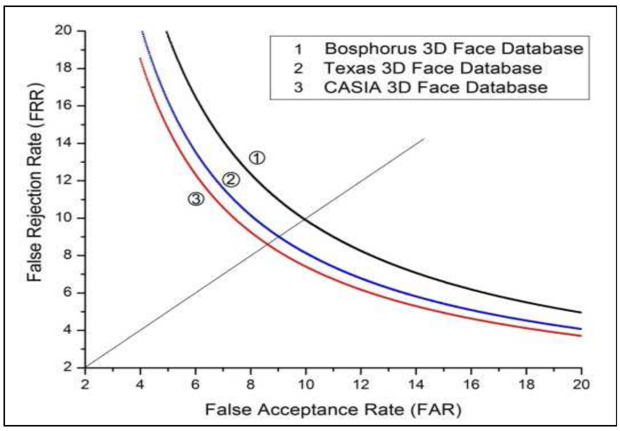

Figure. 4. Receiver operating characteristic (ROC) curves for the proposed method, experimented with Bhosphorus, Texas and CASIA 3D face databases yielding equal error rates 9.7914, 8.9264 and 8.5286 respectively.

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

No. of Eigen Components	RT + Symbolic PCA[17]	RT+PCA +LDA [17]	RT+ Symbolic LDA [18]	RT+FDA [24]	RT+ Symbolic FDA **Proposed Method**
5	62.00%	61.60%	68.00%	69.00%	71.00%
10	78.00%	77.90%	83.50%	85.00%	88.00%
15	85.50%	85.10%	88.00%	91.20%	93.00%
20	91.00%	91.20%	94.00%	95.00%	96.80%
25	95.00%	94.20%	97.00%	97.00%	97.90%
30	96.00%	95.91%	98.00%	98.50%	98.80%
35	96.50%	97.90%	98.00%	98.50%	99.00%
40	97.00%	99.16%	99.50%	99.66%	**99.80%**

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

Method	Recognition Accuracy
Faltemier et al. [19]	94.90%
Maurer et al. [20]	95.80%
Kakadiaris et al. [21]	97.00%
H. usken et al. [22]	97.30%
Mian et al.[23]	99.30%
Proposed Method	**99.80%**

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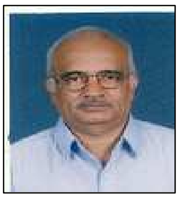

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