

# 3D Face Recognition using Radon Transform and Symbolic LDA

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## ABSTRACT

Many recent events, such as terrorist attacks, have exposed the serious weaknesses in most sophisticated security systems. 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, the novel method for three dimensional (3D) face recognition using Radon transform and Symbolic LDA based features of 3D range face images is proposed. 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 99.50% recognition performance with reduced computational cost, which compares well with other state-of-the-art methods.

## Keywords:

3D face recognition, range image, radon transform, Symbolic LDA.

## 1. INTRODUCTION

Many recent events, such as terrorist attacks, have exposed the serious weaknesses in most sophisticated security systems. Various government agencies are now more motivated to improve security data systems based on body or behavioral characteristics, often called biometrics. In general, biometric systems process raw data in order to extract a template which is easier to process and store, but carries most of the information needed. It is a very attractive technology, because it can be integrated into any application requiring security or access control, effectively eliminating risks associated with less advanced technologies that are based on what a person has or know rather than whom a person really is. Perhaps the most common biometrics are finger-prints and iris, but many other human characteristics have been studied in last years: finger/palm geometry, voice, signature, face.

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 an image[1,2]. 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, 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 a suitable image data for face recognition, but the data is complex and difficult to handle. A range image can be a good alternative to a 3D mesh image. A range image contains the structural information of a face and also is simple to utilize for face recognition.

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. For example, a nose tip is the closest point to the camera on a face, so it has the highest numerical value. Range images have some advantages over 2D intensity images and 3D mesh images. First, range images are robust to the change of illumination and color because the value on each point represents the depth value which does not depend on illumination or color. 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.

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[1-4,10,11]. Gupta et al.[5] 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.[6] constructed many 3D models as registered templates, and then they matched 2.5D images (original 3D data) to these models using iterative closest point (ICP). Chang et al. [7] 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. The symbolic data analysis[12,13] deals with interval-valued variables, which capture the face image variabilities due to changes in the illumination, orientation and expressions. Hire-



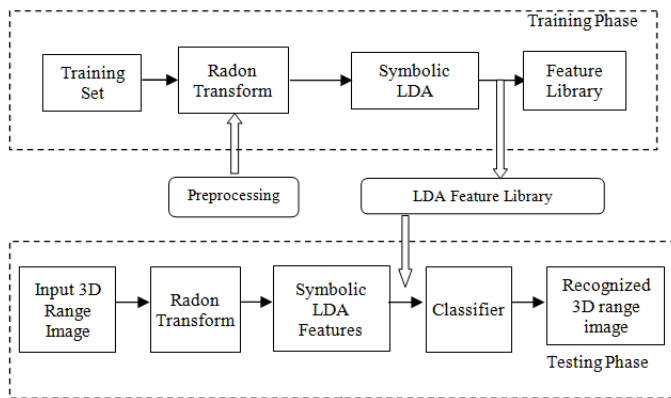


Fig. 1. Overview of proposed framework

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

where  $s=1,2,\dots,p$  and

$$B_{test} = [Z_{(test)1}, Z_{(test)2}, \dots, Z_{(test)p}].$$

### 3.3 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  $I1$  from the training set containing  $M$  images.
- (2) Apply Radon transform, from  $0^\circ$  to  $180^\circ$  orientations (in steps of  $h$ ), to the input range image  $I1$  yielding a binary image  $I2$ .
- (3) Superpose the binary image  $I2$  obtained in the Step 2 on the input range image  $I1$  to obtain the cropped facial range image  $I3$ .
- (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  $w_1, w_2, \dots, w_p$  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  $w_1, w_2, \dots, w_p$  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  $Z1$ .
- (2) Apply Radon transform, from  $0^\circ$  to  $180^\circ$  orientations (in steps of  $h$ ), to the input range image  $Z1$  yielding a binary image  $Z2$ .
- (3) Superimpose the binary image  $Z2$  on  $Z1$  to obtain the cropped facial image  $Z3$ .
- (4) Compute the symbolic weights  $w_i^{test}, i = 1, 2, \dots, p$ , for the test image  $Z1$  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.

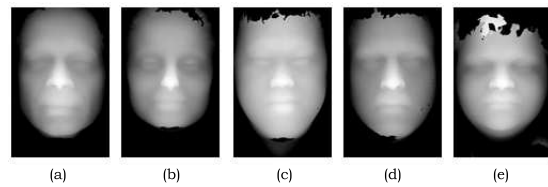


Fig. 2. Sample range images of the training set.

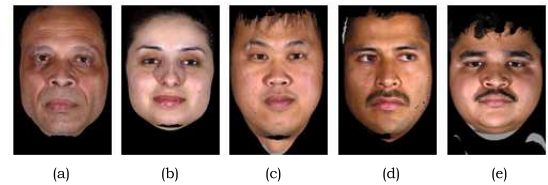


Fig. 3. The facial texture images corresponding to the training range images of the Figure 2

- (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

For experimentation, the Texas 3D face database [8] is considered. 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 recognition rates obtained by the proposed (RT+Symbolic LDA) approach is compared with PCA (alone), RT+PCA[16], RT+PCA+LDA[17] and Symbolic PCA[18] methods and the comparison 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 99.50% for 5 LDA components 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 methods. The RT+Symbolic LDA produces the classification results with same accuracy as that of RT+PCA+LDA is observed, but with reduced computational cost.

## 5. CONCLUSION

In this paper, a novel method for three dimensional (3D) face recognition using Radon transform and Symbolic LDA based features of 3D range face images is proposed. 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 99.50% recognition performance with reduced complexity and a

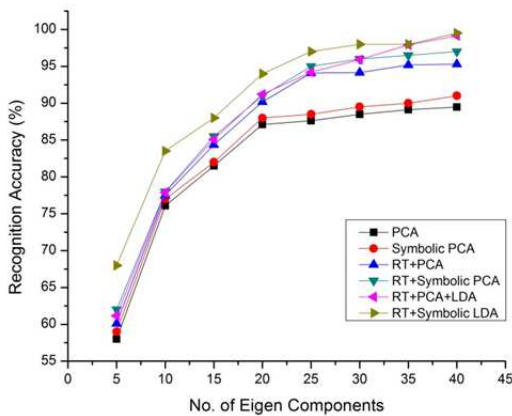


Fig. 4. The recognition accuracy (%) versus the number of eigenfaces obtained for the proposed method and the other methods.

Table 1. Performance comparison of PCA, Symbolic PCA, RT+PCA and RT+Symbolic PCA in terms of recognition rates(%)

No. of Eigen Components	PCA [16]	Symbolic PCA [18]	RT + PCA [16]	RT + Symbolic PCA[18]	RT+PCA +LDA [17]	RT+ Symbolic LDA (Proposed)
5	58.50	59	60.10	62	61.6	68
10	76.10	77	77.50	78	77.90	83.50
15	81.50	82	84.36	85.5	85.10	88
20	87.10	88	90.19	91	91.20	94
25	87.61	88.5	94.10	95	94.20	97
30	88.50	89.5	94.16	96	95.91	98
35	89.11	90	95.20	96.5	97.90	98
40	89.47	91	95.30	97	99.16	99.50

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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