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# 3D Face Recognition Using Modified PCA Methods

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***Abstract*—**In this paper we present an approach for 3D face recognition based on extracting principal components of range images by utilizing modified PCA methods namely 2DPCA and bidirectional 2DPCA also known as $(2D)^2$ PCA.A preprocessing stage was implemented on the images to smooth them using median and Gaussian filtering. In the normalization stage we locate the nose tip to lay it at the center of images then crop each image to a standard size of 100*100. In the face recognition stage we extract the principal component of each image using both 2DPCA and $(2D)^2$ PCA. Finally, we use Euclidean distance to measure the minimum distance between a given test image to the training images in the database. We also compare the result of using both methods. The best result achieved by experiments on a public face database shows that 83.3 percent is the rate of face recognition for a random facial expression.

***Keywords*—**3D face recognition, 2DPCA, $(2D)^2$ PCA, Range image

## I. Introduction

FACE recognition has become one of the most important fields in automated biometric identification systems [1]. The vast majority of face recognition research has focused on the use of two dimensional intensity images [1],[2]. However face recognition techniques from 2D images are affected strongly by variations in pose and illumination. Even though the latest 2D face recognition systems have achieved good performance in constrained environments they are still unable to deal with the problems mentioned above i.e. changes in head poses and illumination conditions [3],[4].

Since the human face is a 3D object utilizing the 3D face information can improve the face recognition performance considerably. Recently with the development of the 3D data acquisition systems, 3D face capture is becoming faster and cheaper. Early work on 3D face recognition was launched a decade ago and a few approaches have been reported about face recognition using 3D data acquired by a 3D sensor. Especially most works mentioned above used range images to evaluate the face recognition method[5],[6],[7],[8],[9]. Indeed, in range images instead of brightness or color information, the depth at which the ray associated with each pixel first intersects the scene observed by a camera, in other words it gives us the depth map of the object which is a function giving for each pixel of the image the depth of the corresponding 3D point, i.e. the distance of the point from the camera plane. The advantages of range images are the explicit representation of 3D shapes, invariance under change of color and reflectance properties of the object [5].

Figure 1 shows our step-by-step diagram for face recognition by utilizing range images. First a frontal range image is subjected to a preprocessing stage in which the background and needless parts of face is eliminated by thresholding the depth map of the 3D image. Then a surface smoothing stage is carried out to prevent variations giving false matching result. The resultant smoothed image is normalized and then aligned with the coordinate system centered at the detected nose point. Next step is dimension reduction step in which each image is described by its principal component using modified PCA methods.

The resultant principal components are used as feature vector in classification stage to calculate the similarity between to facial images. The nearest neighbor classifier is used in the matching process.

The remainder of this paper is organized as follows: section 2 introduces the preprocessing module, including the face detection stage, surface smoothing and nose localization. In section 3 we briefly review modified PCA methods for dimension reduction and also the neighbor classifier method for classification will be explained. Section 4 illustrates the experimental results using a public 3D face database to test the identification performance. Conclusion and future works are discussed in section 5.

## II. Preprocessing and Normalization Stage

### *A. Image thresholding*

The main part of an image which can be used to identify the owner of the image is the face part, but the range images captured by a laser scanner may consist of other parts including neck and shoulders. So we should specify the face part only. To do this we use Otsu's method for image thresholding.

Otsu suggested a criterion by which the best threshold for images with bimodal histograms can be determined [10]. The criterion states that the threshold should be chosen in such a way that minimizes the weighted sum of within group variances for the two groups that results from separating the

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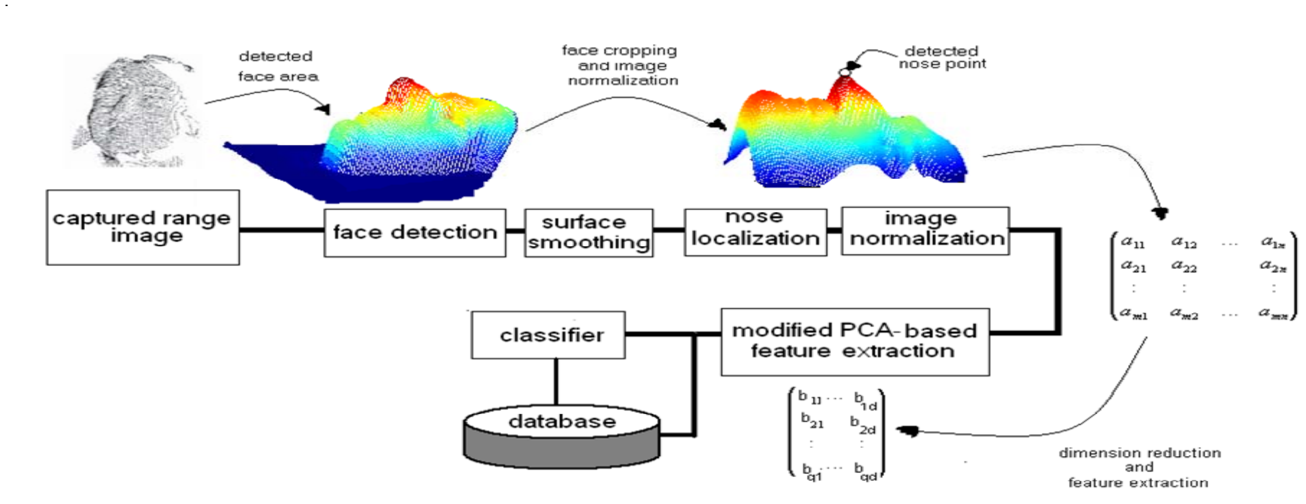


Fig. 1 Block diagram for 3D face recognition from range data



gray levels at the threshold value [10]. Figure 2 shows a raw face image and the resultant thresholded version of it using Otsu's method.

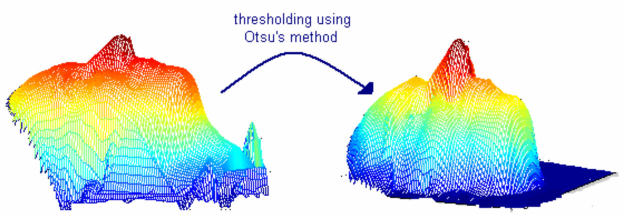


Fig. 2 A raw face image and its thresholded version

### *B. Surface Smoothing and Nose Localization*

The range images captured by laser scanner sometimes have some sharp spikes and noise that should be removed because it can deteriorate the final result. To do this we can apply median filtering. After this step the image is ready for normalization. In the normalization stage, first the nose tip must be localized to lay at the center of the image. it's an easy task because in the smoothed data usually the nose tip is the closest part of the face to the 3D scanner, so it has the highest depth value among all the facial points. after detecting the nose all the images in the database are normalized to a standard 100*100 pixels in size and then aligned so that the nose lies exactly at the center of each image at the (50,50) x-y coordinate. Now the images are ready for dimension reduction and feature extraction.

## III. Introduction to Modified PCA Methods

### *A. 2DPCA*

Suppose A denote m*n depth map matrix and X denotes an n-dimensional unitary column vector, the idea is to project image A onto X by the following transformation:

$$Y=AX \tag{1}$$

Let us define the image covariance matrix as follows:

$$G = E[(A - E(A))^T (A - E(A))] \tag{2}$$

Suppose that the number of training samples is N, the jth training image is denoted by $A_j$ (j=1,2,3,…,N) and the average image matrix is denoted by $\overline{A}$ then G can be evaluated by :

$$G = \frac{1}{N}\sum_{i=1}^{N}(A_i - \overline{A})^T (A_i - \overline{A}) \tag{3}$$

The optimal projection axis $X_{opt}$ is the eigenvector of G corresponding to the largest eigenvalue.

The optimal projection vectors of 2DPCA, $X_1, X_2, \ldots, X_d$ are choosed for feature extraction. For a given image sample A, let:

$$Y_k = AX_k \quad k=1,2,\ldots,d \tag{4}$$

Then we obtain a family of projected feature vectors $Y_1, Y_2, \ldots, Y_d$ which are called the principal component. The feature vectors form an m*d feature matrix which will be used in the classification stage.

The projection vectors $X_1, X_2, \ldots, X_d$ and the principal component $Y_1, Y_2, \ldots, Y_d$ can be used to reconstruct the depth map of the images;

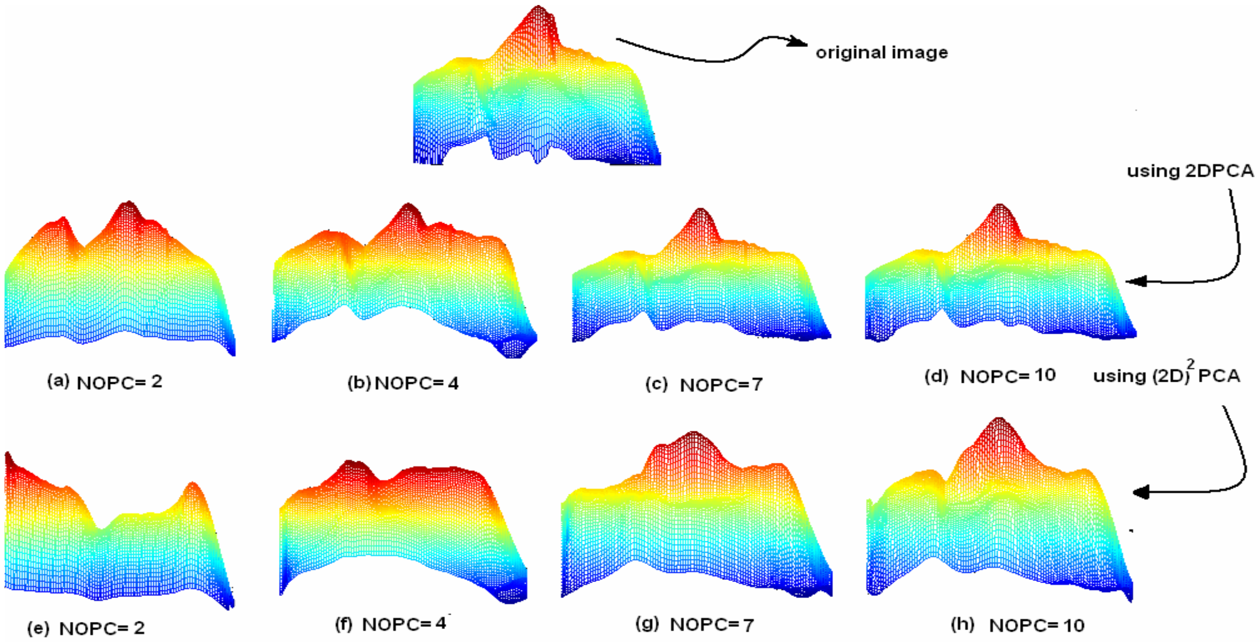


Fig. 3 An original image and its reconstructed versions (NOPC=number of principal component)

suppose U=[ $X_1, X_2, \ldots, X_d$ ] and V=[ $Y_1, Y_2, \ldots, Y_d$] then the reconstructed depth map of the image can be obtained using equation (5):

$$\tilde{A} = VU^T \tag{5}$$

In which $\tilde{A}$ is the reconstructed image. If d=N then the reconstructed image will be the same as the original image A, i.e. $A = \tilde{A}$

*B .Bidirectional 2DPCA*

In bidirectional 2DPCA in addition to principal component obtained from G using equation (3) we use an alternative definition for image covariance matrix as follows:

$$G' = \frac{1}{N}\sum_{i=1}^{N}(A_i - \bar{A})(A_i - \bar{A})^T \tag{6}$$

Similarly the optimal projection matrix $Z_{opt}$ can be obtained by computing the eigenvectors $Z_1, Z_2, \ldots, Z_q$ of equation (6) corresponding to the q largest eigenvalue i.e. $Z_{opt}$=[ $Z_1, Z_2, \ldots, Z_q$] .

Suppose we have obtained the projection matrices X and Z. now new definition for principal component of image A can be obtained by projecting A onto X and Z by the following equation:

$$C = Z^T A X \tag{7}$$

Now matrix C is the principal component of image A and is our new feature matrix. By comparing 2 feature matrices reconstruct the original image using the following equation:

$$\tilde{A} = ZCX^T \tag{8}$$

Figure (3) shows some of reconstructed images using equations (5), (8) and different number of principal component. we can see that in both methods as the number of eigenvectors is increased the reconstructed images become clearer.

*C. Classification stage*

After projecting each training image $A_k$ (k=1,2,…,M) onto X and Z, first we use equation(4) to find feature matrix Y by 2DPCA method and then equation(7) to find feature matrix C by (2D)$^2$PCA method; then a nearest neighbor classifier is used for classification. Here the distance between 2 arbitrary feature matrices $M_p$ and $M_q$ with arbitrary size of a*b is defined by:

$$d(M_p, M_q) = \| M_p - M_q \| = \sqrt{\sum_{i=1}^{a}\sum_{j=1}^{b}(M_p^{(i,j)} - M_q^{(i,j)})^2} \tag{9}$$

## IV. EXPERIMENTAL RESULTS

In this section we compare the results of implementing 2DPCA and (2D)$^2$PCA on Gavab 3D face database [14]. All of our experiments are carried out on a PC machine with 2.8GHz CPU. Also all of the simulation was carried out using Matlab version R2006b.

Gavab contains 540 3D facial surfaces corresponding to 60 individuals. For each person there are nine different images, two neutral frontal images, four neutral images with pose (looking left, right, up, down) and three frontal images in which the subject presents different and accentuated facial expression. In our experiments for each person we considered the two neutral frontal images and the random gesture and also accentuated laugh as gallery and the smile image as the probe image.

Table 1 compares the result of exploiting the mentioned methods when utilizing different number of eigenvalue. Comparisons include recognition accuracy, dimension of feature vectors and its influence on recognition accuracy.

TABLE I COMPARISON OF RECOGNITION RATE AND RECOGNITION TIME BETWEEN 2DPCA AND $(2D)^2$PCA IN 3D FACE RECOGNITION

| NOPC | recognition rates | | running time | |
|---|---|---|---|---|
| | 2DPCA | $(2D)^2$PCA | 2DPCA | $(2D)^2$PCA |
| 5 | 80 | 70 | 1.08 | 0.6 |
| 6 | 78.3 | 73.3 | 1.18 | 1.1 |
| 7 | 83.3 | 76.7 | 1.3 | 1.18 |
| 8 | 83.3 | 80 | 1.43 | 1.29 |
| 9 | 81.7 | 81.7 | 1.51 | 1.42 |
| 10 | 81.7 | 81.7 | 1.63 | 1.5 |
| 20 | 81.7 | 81.7 | 2.63 | 2.4 |
| 30 | 81.7 | 81.7 | 3.62 | 3.25 |
| 40 | 81.7 | 81.7 | 4.62 | 4.15 |

We compared the rate of these two methods with other methods that used the same dataset. Two different approaches for 3D face recognition were presented by Moreno *et al* .in [8],[9]and were evaluated using GavabDB. In [8] they segmented the range images into isolated subregions using the mean and Guassian curvature. Then, they extracted 86 discriptors such as the areas, the distances, the angles, and the average curvatures of subreginos. They selected 35 best features and utilized them for face recognition, they achieved 62% recognition rate for smile expression. also in [9] they achieved 76.2 and 77.9 when using PCA and SVM matching scheme, under expressions and slight face rotation.

So we can conclude that in 3D face recognition area utilizing 2DPCA and $(2D)^2$PCA can perform better because they increase the recognition rate considerably.

## V. CONCLUSION AND FUTURE WORKS

In this paper we present a method for 3D face recognition using range images. In the feature extraction stage we used 2DPCA and $(2D)^2$PCA, which were previously exploited on 2D intensity images. The Gavab database was utilized to test our method. As we mentioned in the conclusion section in comparison with other methods using the same database, the proposed method resulted a higher recognition rate. Future works can include experiment this method on other 3D face databases.

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