3D Face Recognition Based On Extracting PCA Methods

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Abstract
we present here an approach for 3D face recognition based on extracting principal components of range images by modified PCA methods namely Two dimensional PCA and bidirectional two dimensional PCA also known methods. A preprocessing stage was implemented on the images to smooth them using median 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 Two dimensional PCA and bidirectional two dimensional 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.

***Keywords*—**3D face recognition, Two DPCA, Bidirectional 2 DPCA, Image database

Introduction
Much of the work in computer recognition of faces has focused on detecting individual features such as the eyes, nose, mouth, and head outline, and defining a face model by the position, size, and relationships among these features. Beginning with Bledsoe's [12] and Kanade's [13] early systems, a number of automated or semi-automated face recognition strategies have modeled and classified faces based on normalized distances and ratios among feature points. Recently this general approach has been continued and improved by the recent work of Yuille et al [14]. Face recognition has received significant attention in the past decades due to its potential applications in biometrics, information security, law enforcement, etc. By far, numerous methods have been suggested to address this problem [1]. Among them, principal component analysis (PCA) turns out to be very effective [2]. Recently, a PCA closely-related method, independent component analysis (ICA) [3], has also been applied to face recognition. ICA can be viewed as a generalization of PCA since it concerns not only second-order dependencies but also high-order dependencies between variables. The previous researchers [4, 5], however, all use the standard PCA as the baseline algorithm to evaluate ICA-based face recognition systems. The initial success of eigenfaces popularized the idea of matching images in compressed subspaces. Researchers began to search for other subspaces that might improve performance. One alternative is Fisher's linear discriminate analysis (LDA, a.k.a. "fisher faces") [6]. For any N-class classification problem, the goal of LDA is to find the N-1 basis vectors that maximize the interclass distances while minimizing the intraclass distances. At one level, PCA and LDA are very different: LDA is a supervised learning technique that relies on class labels, whereas PCA is an unsupervised technique. Nonetheless, in circumstances where class labels are available either
technique can be used, or LDA has been compared to PCA in several studies [7]. Principal Component Analysis is a standard technique used to approximate the original data with lower dimensional feature vectors [8]. The basic approach is to compute the eigenvectors of the covariance matrix, and approximate the original data by a linear combination of the leading eigenvectors. The mean square error (MSE) in reconstruction is equal to the sum of remaining Eigen values. The feature vector here is the PCA projection coefficient. PCA is appropriate when the samples are from one class or group (super class). In real implementation, there are two ways to compute the eigen values and eigenvectors: SVD decomposition and regular Eigen computation. For efficient way to compute or update the SVD, please refer to [9, 10]. In many cases, even though the matrix is full rank matrix, the large condition number will create a numerical problem. The distance measure used in the matching could be a simple Euclidean or a Weighted Euclidean distance. It has been suggested that the weighted Euclidean will give better classification than the simple Euclidean distance [11]. Moreover this technique can also be applied for the purpose of Facial Expression Analysis. Most approaches to automatic facial expression analysis attempt to recognize a small set of prototypic emotional facial expressions, i.e., fear, sadness, disgust, anger, surprise, and happiness (e.g., [15], [16];). This practice may follow from the work of Darwin [17], and more recently Ekman [18], who suggested that basic emotions have corresponding prototypic expressions. From several methods for recognition of facial gestures, the facial action coding system (FACS) [19] is the best known and most commonly used in psychological research [20]. The changes in the facial expression are described with FACS in terms of 44 different action units (AUs), each of which is anatomically related to the contraction of either a specific facial muscle or a set of facial muscles. Along with the definition of various AUs, FACS also provides the rules for AU detection in a face image.

PCA: Principal Components Analysis

PCA commonly referred to as the use of eigenfaces, is the technique pioneered by Kirby and Sirivich in 1988. With PCA, the probe and gallery images must be the same size and must first be normalized to line up the eyes and mouth of the subjects within the images. The PCA approach is then used to reduce the dimension of the data by means of data compression basics and reveals the most effective low dimensional structure of facial patterns. This reduction in dimensions removes information that is not useful and precisely decomposes the face structure into orthogonal (uncorrelated) components known as eigenfaces. Each face image may be represented as a weighted sum (feature vector) of the eigenfaces, which are stored in a 1D array. A probe image is compared against a gallery image by measuring the distance between their respective feature vectors. The PCA approach typically requires the full frontal face to be presented each time; otherwise the image results in poor performance. The primary advantage of this technique is that it can reduce the data needed to identify the individual to 1/1000 th of the data presented.

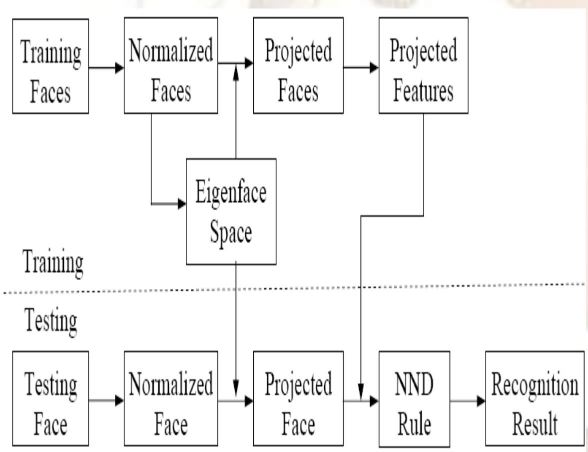


Fig 1 Flowchart for PCA PREPROCESSING AND NORMALIZATION STAGE

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 [21]. 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 gray levels at the threshold value [21]. Figure 2 shows a raw face image and the resultant thresholded version of it using Otsu's method.

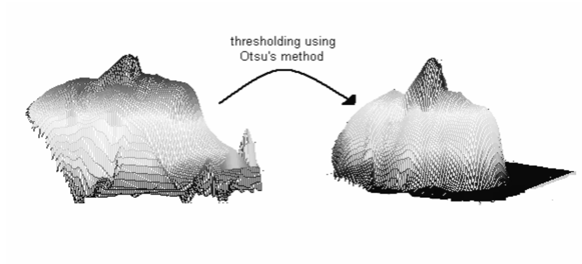


Fig. 2 A raw face image and its thresholded version

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. Two Dimensional PCA Method

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

$$Y=AX \qquad (1)$$

Let us define the image covariance matrix as follows:

$$G=[(A-E(A)^T))(A-E(A))] \qquad (2)$$

Suppose that the number of training samples is N, the jth training image is denoted by

Aj j=1,2,3,…,N) and the average image matrix is denoted by $\bar{A}$ then G can be evaluated by :

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

The optimal projection axis Xopt is the eigenvector of G corresponding to the largest eigenvalue.
The optimal projection vectors of 2DPCA, X1,X 2,…,Xd are choosed for feature extraction. For a given image sample A, let:

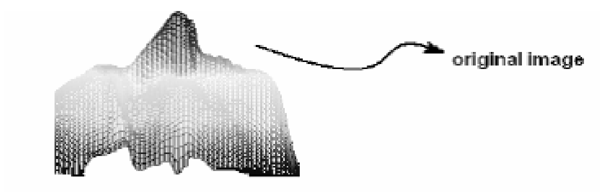
$$Y_k=AX_k \quad k=1,2,\ldots,d \qquad (4)$$

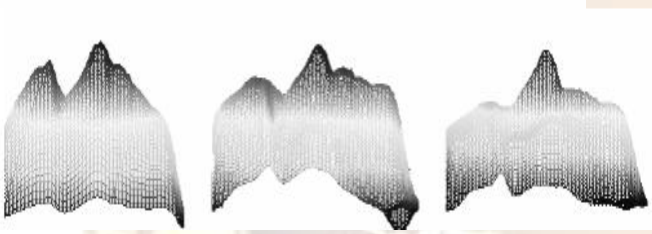
Then we obtain a family of projected feature vectors Y1,Y2,…,Yd which are called the principal component. The feature vectors form an m*d feature matrix which will be used in the classification stage. The projection vectors X1,X 2,…,Xd and the principal component Y1,Y2,…,Yd can be used to reconstruct the depth map of the images.

suppose U=[X1,X 2,…,Xd] and V=[Y1,Y2,…,Yd] then the reconstructed depth map of the image can be obtained using equation (5):

$$\tilde{A}=VU^T \qquad (5)$$

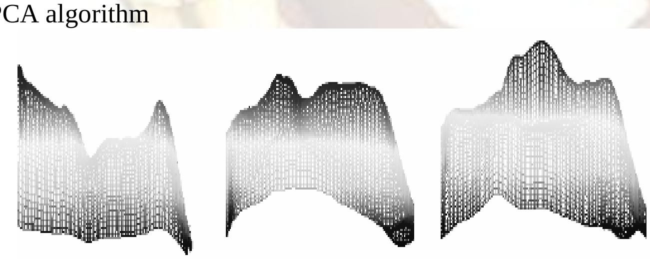
In which $\tilde{A}$ is the reconstructed image. If d=N then the reconstructed image will be the same as the original image A,
i.e. $A = \tilde{A}$





(a) NOPC=2 (b) NOPC=4 (c) NOPC=6

Fig (a) (b) & (c) are constructed using two dimensional PCA algorithm



(d) NOPC=2 (e) NOPC=4 (F) NOPC=6

Fig (d) (e) & (f) are constructed using bidirectional two dimensional PCA algorithm

Fig-3 Original image & Reconstructed versions (NOPC=number of principle component)

B .Bidirectional two dimensional PCA

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:

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

Similarly the optimal projection matrix Zopt can be obtained by computing the eigenvectors Z1, Z2, Zq of equation (6) corresponding to the q largest eigenvalue i.e. Zopt=[Z1,Z2,…,Zq] . 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:

$$C=Z^T AX \qquad (7)$$

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:

$$\tilde{A}=ZCX^T \qquad (8)$$

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.

EXPERIMENTAL RESULTS

In this we compare the results of implementing 2DPCA and bidirectional 2DPCA on Gavab 3D face database [23]. 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. 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 bidirectional 2DPCA can perform better because they increase the recognition rate considerably.

NOPC	Recognition Rate		Running Time	
	2DPCA	Bi 2DPCA	2DPCA	Bi 2DPCA
5	78	69	1.05	0.5
6	76.3	72.3	1.15	1
7	82.3	75.4	1.2	1.15
8	82.3	79	1.4	1.25
9	80.5	80.5	1.48	1.4
10	80.5	80.5	1.61	1.3
20	80.5	80.5	2.61	2.2
30	80.5	80.5	3.6	3.2
40	80.5	80.5	4.5	4.1

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

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, 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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