3D FACE RECOGNITION TECHNIQUES - A REVIEW

Preeti B. Sharma*, Mahesh M. Goyani**

*(Department of Information Technology, Gujarat Technological University, India)
**(Department of Computer Engineering, Gujarat Technological University, India)

ABSTRACT

In this paper, the exploration of new face recognition technology that is 3D face recognition is being analyzed. Face Recognition is widely used for security at many places like airport, organizations, many devices etc. The challenges faced in 2D face recognition technology is been solved through various approaches mentioned in the paper. The various implementation approaches widely accepted is been discussed. Each process in the face recognition consists of sub-process and the sub-process is categorized into registration, representation, extraction of discriminative features.

***Keywords*: Face recognition, Eigen-Surface, Fisher-surface, Euclidean distance

1. INTRODUCTION

Face Recognition is the process to identify the input test face from the stored dataset. Face Recognition Technology (FRT) is used in several disciplines such as image processing, pattern recognition, computer vision etc. in which research is been continuously carried out. More recently face recognition as a “biometric technology (whereby the face is physiological trait that uniquely identifies an individual) has become a hot topic of modern day research as a result of the growing pressure to exploit faces as a means of identification from both the commercial and law enforcement. Research in automated methods of face recognition are said to have begun in the 1960s with the pioneering work of Chapella [1], in which he presented a critical survey of existing literature on human and machine recognition of faces. Automated face recognition technologies are also in use in both the civilian and Law enforcement areas.Face Recognition fall into two categories: verification and identification. Face verification is a 1:1 match that matches a face against the template face images whose identity is to be claimed. Face identification is 1:N problem that compares a query face image against all image templates in face database to determine the identity of the query face. During 1964 and 1965, Bledsoe, along with Helen Chan and Charles Bisson [2], worked on using computers to recognize human faces at Stanford institute. Bledsoe designed and implemented a semi-automatic system. Some face coordinates were selected by a human operator, and then computers used this information for recognition. He described most of the problems that even 50 years later Face Recognition still suffers - variations in illumination, head rotation, facial expression, and aging. Researches on this matter still continue, trying to measure subjective face features as ear size or between-eye distance. For instance, this approach was used in Bell Laboratories by A. Jay Goldstein, Leon D. Harmon and Ann B. Lesk [3] in which how well can human faces be identified by humans and by computers, using subjectively judged "feature" descriptions like long ears, wide-set eyes. Although the first fully functional implementation of an automated faces recognition system was not produced until Kanade’s paper [4] in 1977. They described a vector, containing 21 subjective features like ear protrusion, eyebrow weight or nose length, as the basis to recognize faces using pattern classification techniques. In the last five years, a rapid increase for the need to design 3D face recognition algorithms has taken place both in academy and industry. However, it is clearly visible that the 3D face recognition technology is at the beginning steps. The motivation to use 3D technology was to overcome the disadvantages of 2D face recognition systems that arise especially from significant pose, expression and illumination differences. However, with the exception of few recent works, most of the 3D systems generally study controlled frontal face recognition. With the construction of bigger 3D face databases that contain enough samples for different illumination, pose, and expression variations, it is expected to develop more realistic 3D face recognition.

Rest of the paper is organized as follow. Next section describes the key challenges of face recognition techniques. We have given some details about 3D faces in section 3, followed by the review work in section 4, in which we have discussed various categories of the algorithms for face recognition. Later section is discussion and conclusion

2. CHALLENGES IN FRT

There are two major challenges faced during the testing, those are illumination problem and pose variation problem.
Both these problems are serious and cause the degradation of the existing system. These problems can be formulated and a common approach could be followed by sequencing the operations face detection, face normalization and inquire database

2.1 Illumination Problem

Same image may appear differently due to illumination condition. If the illumination induced is larger than the difference between the individuals, system may not be able to recognize the input image. It has been suggested that one can reduce variation by discarding the most important eigenface. And it is verified in [5] that discarding the first few eigenfaces seems to work reasonably well. Many of the methods were suggested by researchers which ultimately led to the result that the methods were illumination-invariant and the measure of the same object changes when illumination changes.

An illumination subspace can be constructed but one drawback of this method is that many of the faces of one person are needed to construct the subspace. Methods have been developed to solve the illumination problem the approaches have been divided into four categories: First is heuristic methods including and discarding the leading principal components. Second, image comparison methods where various image representations and distance measures are applied. In class-based methods where multiple images of one face under a fixed pose but different lighting conditions are available. Finally in model-based approaches 3D models are employed.

2.2 Pose Problem

Researchers have proposed various methods to handle the rotation problem. Basically they can be divided into three classes: *a).* multiple images based methods: when multiple images per person are available. This method is based on illumination cone to deal with illumination variation. For variations due to rotation, it needs to completely resolve the GBR (generalized-bas-relief) ambiguity when reconstructing 3D surface. *b).* hybrid methods: when multiple training images are available during training, but only one database image per person is available during recognition. Numerous algorithms of the second type have been proposed and are by far the most popular ones. Possible reasons for this are: i) It is probably the most successful and practical method up to now, ii) It utilizes prior class information., and *c).*single image/shape based methods when no training is carried out. In these methods, face shape is usually represented either by a polygonal model or a mesh model which simulates issue..

3. DATASET DESCRIPTION

This section gives the description of the 3D database available on which the operations are being performed for 3D face recognition.

3.1 FEI Dataset

The FEI database consists of 14 images for each 200 individuals there are 2800 images. All the images are colored and are taken against homogenous background and the images are rotated to the degree of 180.The original size of each image is 640 x 180 pixels. The images of the student and staff are taken between 19 and 40 and the numbers of male and female images are exactly the same. The images are taken between June 2005 and March 2006 and are Brazilian database.

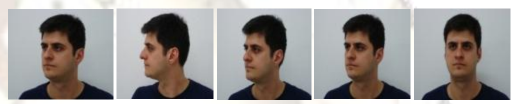

Fig 1. Sample Images for FEI dataset

3.2 TEXAS 3D Dataset

Texas 3D Face Recognition consist of 1149 pairs of facial color and range images of 105 subjects of adult human. The images are acquired on very high resolution while acquiring each image the color and range images were captured simultaneously and therefore were perfectly registered.

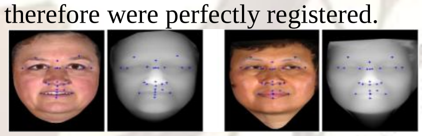

Fig 2 . Sample Images for TEXAS 3D dataset

3.3 3D FERET Dataset

A 3D Face Database has been gathered to facilitate research into 3D face recognition. Currently, little three-dimensional face data is publicly available and nothing towards the magnitude of data that we require for development and testing of our recognition systems. Therefore, we began populating our own 3D face database. Ten facial surfaces of 97 different people were captured, under the conditions shown below.

Fig 3 Sample Images for FERET Dataset

3.4 3D GAVAB Dataset

The GAVAB database consists of 549 3D images of facial surfaces. There are 61 individuals in which 45 male and 16 female and total of 9 images of each person the images of people between age 18 and 40 are taken. In, the 9 images corresponding to each individual are: 2 front views with neutral expression, 2 x-rotated views (±30º, looking up and looking down respectively) with neutral expression, 2 y-rotated views (±90º, left and right profiles respectively) with neutral expression and 3 frontal gesture images (laugh, smile and a random gesture chosen by the user, respectively).

4. BACKGROUND AND RELATED REVIEW

The 3D Face recognition algorithm can be classified as shown in fig. 1

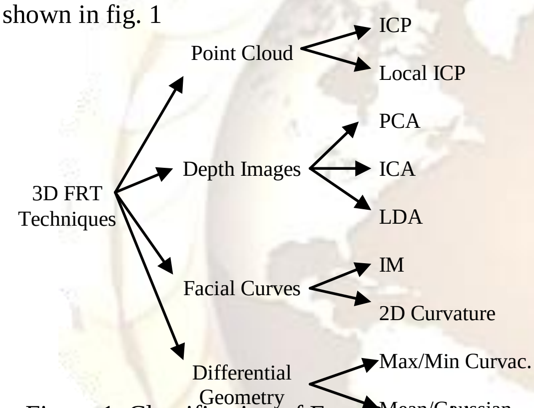

Figure 1. Classification of Face Recognition Techniques

4.1 Point Cloud Approach

Point cloud based approach consists of human facial surface in 3D point cloud representation. In this from the facial surface only (x, y, z) co-ordinates of the sample points are used. This approach is widely accepted because of its generality and simplicity. Generality because almost every 3D acquisition device produces (x, y, z) co-ordination without any higher level of information. Simplicity because the points coordinate if sampled with good accuracy is simple and sufficient to represent a complex surface. The point cloud approach requires the alignment and registration of facial surfaces before the matching module because the similarity of different facial surfaces as opposed by more general 3D objects classes.

4.1.1 Iterative Closest Point (ICP)

The ICP is developed to end the emphasis on correct alignment of different facial surfaces of most 3D object identification system and algorithm. ICP tries to find the best rotation and translation parameters to align one model to the other one iteratively. The main drawback or the limitation of ICP algorithm is that it cannot handle non-rigid deformations. When two input model are considered the ICP can find the dissimilarity in quality of alignment. Therefore most of the 3D system use point sets and utilize the ICP dissimilarity in the quality of alignment .Therefore most of the 3D system use point set and utilize the ICP dissimilarity as the matching metric.

The ICP is used for the shape matching algorithm and the face matcher. The basic principle of the ICP is to take the test image align it, and select the training image ID that produces the lowest ICP alignment error. Many algorithms based on the ICP are used but aligning each training image with the probe image at the identification phase becomes computationally expensive.

The ICP algorithm executes on the steps of face recognition process: The first step is the preprocessing step is to remove the extraneous surface that are not used for verification purpose. The next step is Registration is the task of face comparison is a non-rigid registration problem due to inherent elasticity in human skin due to motion available such as human jaw. The problem can be solved by considering only small sections of face and performing alignment to the subsections. The next step is the feature extraction in which after the range images are aligned, it is possible to extract corresponding feature from the surface and compare them directly. Features such as surface depth and curvature which are extracted from point locations are directly comparable and coincident. The vector of the difference between the features is build and the comparison is created which comprises information on the difference between surfaces.

4.1.2 Local ICP

The local ICP is an extension of ICP based approach. There are two important reasons for using the Local ICP : The one reason is the case in which all facial surface exhibits rigid deformation and second one is matching of the local regions is faster.

4.2 Depth Based Approach

It is very popular to convert 2.5D facial data to a depth image, also called the range image. Each pixel in the depth image represents the distance of the corresponding 3D facial point to the camera. Although some sensors are capable of producing range images directly, point cloud data acquired from sensors is usually converted to yield depth images. During the conversion, some information may be lost. Most importantly, two sources of information loss should be mentioned: Firstly In the surface areas whose normal are almost perpendicular to the camera view, such as the lower nose regions, a significant portion of the depth measurements is generally under-represented in the depth images, and Secondly, 8-bit standard gray-level quantization may lose accuracy information. Another important concern in depth image construction is the conversion of irregularly sampled 3D points to a regular (x, y) grid. To accomplish this task, interpolation methods are generally used.

4.2.1 Principle Component Analysis (PCA)

Face recognition is mainly based on the Principal Component Analysis Principal Component Analysis (PCA, also known as "Eigen surfaces"). In [13], is one of the most known global face recognition algorithm. The main idea is to decorrelate data in order to highlight differences and similarities by finding the principal directions (i.e. the eigenvectors) of the covariance matrix of a multidimensional data.

The steps performed in PCA are: First step includes training phase using the Training Set, in order to generalize the ability of our system and generate eigenvectors. Then we compute the mean image of the training data. Then each Training image is mean subtracted. Then the covariance matrix (C) of the mean-subtracted training data is then computed (T) denotes the matrix transposition operation. The next step consists in finding the eigenvectors e_n and the eigenvalues λ_n of *C*. A part of the great efficiency of the PCA algorithm is to take only the "best" eigenvectors in order to generate the subspace ("*Face Space*") where the gallery images will be projected onto, leading to a reduction of dimensionality. Eigen values are sorted in decreasing order (a higher eigenvalue captures a higher variance, hence more information).The mean image of the Gallery Set is computed. Each mean-subtracted gallery image is then projected onto the "Face Space" spanned by the eigenvectors deriving from the Training Set. This step leads to a simple *dot product.* Scalars ω_k are called "weights" and represent the contribution of each eigenvector for the input image. Thus, for each gallery image, we have a "Weights Vector". The "Weights Matrix" is then generated and stored in the database and will be used during the *recognition step* we focused on. The Recognition takes place in several steps: The dot product is the first basic operation that must be done during the recognition step. A normalized probe image is projected onto the "Face Space", in order to obtain a vector. The second step is the Distance Measure: Once the incoming probe image has been projected onto the Face Space, we have to see whether it is a known face or not. To proceed, we compute the Squared Euclidean Distance (SED) between the weights from the probe image and the Weights Matrix of the entire Face Space: Finally the minimum Euclidean distance is calculated. Assume the ID of the probe image is the l (from 1 to P) and k is the index corresponding to the minimum SED, a subject is considered as a genuine if l=k, otherwise he is considered as an impostor.

4.2.2 Independent Component Analysis (ICA)

In [14], While PCA decorrelates the input data using second-order statistics and thereby generates compressed data with minimum mean-squared reprojection error, ICA minimizes both second-order and higher-order dependencies in the input. It is intimately related to the *blind source separation* (BSS) problem, where the goal is to decompose an observed signal into a linear combination of unknown independent signals. Let **s** be the vector of unknown source signals and **x** be the vector of observed mixtures. If **A** is the unknown mixing matrix, then the mixing model is written as x = As It is assumed that the source signals are independent of each other and the mixing matrix **A** is invertible. Based on these assumptions and the observed mixtures, ICA algorithms try to find the mixing matrix **A** or the separating matrix **W** such that $u = Wx = WAs$ is an estimation of the independent source signals ICA can be viewed as a generalization of PCA.

As previously discussed, PCA decorrelates the training data so that the sample covariance of the training data is zero. Whiteness is a stronger constraint that requires both decorrelation and unit variance. The whitening transform can be determined as **D-1/2RT** where **D** is the diagonal matrix of the eigenvalues and **R** is the matrix of orthogonal eigenvectors of the sample covariance matrix. Applying whitening to observed mixtures, however, results in the source signal only up to an orthogonal transformation. ICA goes one step further so that it transforms the whitened data into a set of statistically independent signals. Signals are statistically independent when the probability density function is equivalent to say that the vectors u is uniformly distributed.Unfortunately, there may not be any matrix W that fully satisfies the independence condition, and there is no closed form expression to find W. Instead, there are several algorithms that iteratively approximate W so as to indirectly maximize independence. Since it is difficult to maximize the independence condition above directly, all common ICA algorithms recast the problem to iteratively optimize a smooth function whose global optima occurs when the output vectors u are independent.

4.2.3 Linear Discriminant Analysis (LDA)

This approach is also known as fisher-surface approach. In LDA we find the linear transformations such that feature cluster are most separable after transformation. We apply PCA and LDA to surface representations of 3D face models, producing a subspace projection matrix, taking advantage of 'within-class' information, minimizing variation between multiple face models of the same person, yet maintaining high class separation. To accomplish this we use a training set containing several examples of each subject, describing facial structure variance (due to influences such as facial expression), from one model to another. From the training set we compute three scatter matrices, representing the within-class (SW), between-class (SB) and total (ST) distribution from the average surface and classes' averages.

The training set is partitioned into *c* classes, such that all surface vectors in a single class are of the same person and no person is present in multiple classes. Calculating eigenvectors of the matrix, and taking the top 250 (number of surfaces minus number of classes) principal components, we produce a projection matrix. This is then used to reduce dimensionality of the within-class and between-class scatter matrices (ensuring they are non-singular) before computing the top *c-1* eigenvectors of the reduced scatter matrix ratio. Finally, the matrix Uff is calculated, such that it projects a face surface vector into a reduced space of c-1 dimensions, in which the ratio of between-class scatter to within class scatter is maximized for all c classes. Like the eigenface system, components of the projection matrix Uff can be viewed as images, as shown in Figure. 4 for the depth map surface space.

Once surface space has been defined, we project a facial surface into reduced surface space by a simple matrix multiplication. The vector is taken as a 'face key' representing the facial structure in the reduced dimensionality space. Face-Keys are compared using either Euclidean or cosine distance measures. An acceptance (facial surfaces match) or rejection (surfaces do not match) is determined by applying a threshold to the distance calculated. Any comparison producing a distance value below the threshold is considered an acceptance.

4.3 Differential Geometry Approach

The differential geometry approaches are invariant to transformation such as translation and rotation is used as common technique for face recognition.

4.3.1 Max/Min Curvature Based Approach

In [12], Curvature of a surface in 3D measures the amount of local bending. Curvature- related descriptors are attractive since they are invariant to rotations, and therefore, they are frequently used in segmenting 3D surfaces. There are different forms of curvature-based descriptors such as minimum/maximum curvatures, their principal directions, mean/Gaussian curvatures, and shape-index values. These descriptors can be used to represent facial surfaces, and are suitable as discriminative features. In principal directions given a point on a surface, there are many curves passing through that point, and each of them has a curvature. Among these curves, two external curves have a special importance: the one that has the minimum curvature, and the one that has the maximum curvature. Therefore, each point on a surface can be characterized by its minimum (·1) and maximum curvature (·2) values, and their directions. These directions are called principal directions (½1, ½2), and are expressed as vectors in 3- space. In [15] Mean and Gaussian curvature values are commonly used surface descriptors in the computer vision community and they are related to the minimum and maximum curvatures.

The advantages of curvature-based technique are: 1) it solves the problem of pose and illumination variation ate the same time. 2) There is a great deal of information in curvature map which we haven't taken advantage of. It is possible to find an efficient way to deal with it. However, there are some inherent problems in this approach: 1) Laser range finder system is much more expensive compared with camera. And this technique cannot be applied to the existing image database. This makes people don't want to choose it if they have another choice. 2) Even though the rage finder is not an issue any more, the computation cost is too high and the curvature calculation is very sensitive to noise. If we use principal component analysis to deal with range data, the error rate probably will be similar while the computation complexity is much lower. 3) We can construct 3D face surface from 2D image instead of expensive range finder. There are a lot of algorithms available to do this. But you will not be able to calculate curvature from reconstructed 3D face surface.

As mentioned earlier, curvature calculation involves second derivative of surface. Only the high-resolution data such as laser range finder makes the accurate curvature calculation possible.

4.3.2 Mean/Gaussian Curvature

In [7], the data of high resolution is produced by rotation laser scanner for accurate curvature calculation. The Gaussian curvature sign is used for face segmentation which allows two surfaces:

convex/concave and saddle regions. Their surface feature extraction contains curvature sign, principal curvature, principal direction, extremes in both principal curvatures. The maximum and minimum curvature at a point defines the principal curvatures.

The directions associated with principal curvatures are the principal directions. The principal curvatures and the principal directions are given by the eigenvalues and eigenvectors of shape matrix. The product of two principal curvatures is Gaussian curvature. And mean curvature is defined by the mean value of two principal curvatures. In practice, because these curvature calculations contain second order partial derivatives, they are extremely sensitive to noise. A smoothing filter is required before calculating curvature. Here, the dilemma is how to choose an appropriate smoothing level. The curvature measurement is useless if the smoothing level is too low, twice derivative will amplify noise. On the other hand, over smoothing will modify the surface features we are trying to measure. In their implementation, they precompute the curvature values using several different levels of smoothing. They use the curvature maps from low smoothing level to establish the location of features. Then, use the prior knowledge of face structure to select the curvature values from the pre-computed set.

4.4 Facial Curve Based Approach

The studies for 3D face recognition emphasize the use of 2D curves extracted from facial surface such as the facial profiles. After these curves are extracted, 2D shape analysis techniques for curves can be used for identification purpose. In this context, a seminal work is presented in [9]. In [9], central and a number of lateral profiles derived from 3D facial surfaces are used for recognition. Matching of the profiles of is carried out using Iterative Conditional Mode (ICM) optimization. Curvature values computed along the profile curves are used as features.

In [8], the extension of the system id made where gray level information is fused with shape features. Zhang et al. [10] also present a profile-based face matcher. Authors propose a system which automatically finds the vertical symmetry profile curve and three points on this curve (Nose Bridge, nose tip, and lower nose point). After finding vertical profile curve, two horizontal profile curves that pass through forehead and cheek regions are computed. Each of these three profile curves are matched separately, and their similarity scores are fused by a weighted sum rule. Weights are determined by the LDA algorithm. It is found that the most discriminative profile curve is the symmetry profile. However, the fusion of three matchers significantly improves the identification/verification accuracy. Experiments done on a 3D face database constructed via 3Q stereo system (32 subjects) illustrates 0.8 per cent EER / 96.9 per cent rank-1 identification rates for neutral-to-neutral case, and 10.8 per cent EER / 87.5 per cent rank-1 identification rates for non neutral case. Feng et al. [11] extracts 35 horizontal and 35 vertical facial curves from the facial surface. Facial curves are represented by integral invariants which are robust to several transformations such as translation, rotation, and scale. After describing curves using invariants, 12 curves are selected according to discriminant analysis and Jensen-Shannon divergence analysis. It is found that 10 of the selected curves are vertical and extracted from the nose and eye regions. PCA-based dimensionality reduction is applied to produce a more compact representation. Recognition experiments on a subset of UND 3D face database (35 subjects) shows that it is possible to obtain 92.57 per cent rank-1 classification accuracy using feature vectors of dimensionality 96.

5. CONCLUSION

We have analyzed the various algorithm of 3D face recognition through which we conclude that 3D face recognition solves the challenges which were found in the result of 2D face recognition mainly the illumination and pose problem through various approaches. The 3D face recognition approaches are still tested on very small datasets. However, the datasets are increasing during the years since better acquisition materials become available. By increasing a dataset, however, the recognition rate will decrease. However, the datasets are increasing during the years since better acquisition materials become available. By increasing a dataset, however, the recognition rate will decrease. So the algorithms must be adjusted and improved before they will be able to handle large datasets with the same recognition performance. Another disadvantage of most presented 3D face recognition methods is that most algorithms still treat the human face as a rigid object. This means that the methods aren't capable of handling facial expressions. In contrast to 3D face recognition algorithms, most 2D face recognition algorithms are already tested on large datasets and are able to handle the size of the data tolerable well. 3D models hold more information of the face, like surface information, that can be used for face recognition or subject discrimination. Another major advantage is that 3D face recognition is pose invariant. Therefore, 3D face recognition is still a challenging but very promising research area.

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