Automatic 3D Face Recognition Using Fourier Descriptors

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Abstract—**3D face recognition is attracting more attention due to the recent development in 3D facial data acquisition techniques. It is strongly believed that 3D Face recognition systems could overcome the inherent problems of 2D face recognition such as facial pose variation, illumination, and variant facial expression. In this paper we present a novel technique for 3D face recognition system using a set of parameters representing the central region of the face. These parameters are essentially vertical and cross sectional profiles and are extracted automatically without any prior knowledge or assumption about the image pose or orientation. In addition, these profiles are stored in terms of their Fourier Coefficients in order to minimize the size of input data. Our approach is validated and verified against two different datasets of 3D images covers enough systematic and pose variation. High recognition rate was achieved.**

Keywords-**2D Face Recognition; 3D Face Recognition; 3D images**

I. INTRODUCTION

Most of the research work done on the area of face recognition was based on 2D representation of facial data, hence a wide range of 2D algorithm are available in the literature [1].

3D face recognition is attracting more attention in the recent years due to two important factors. Firstly, because of the inherent problems with 2D face recognition system that appears to be very sensitive to facial pose variation, variant facial expression, and lighting and illumination. For more information about current work in the 3D recognition area see [2], [3]. Secondly, due to the recent development in the 3D acquisition techniques such as 3D scanners, infrared, and other technologies that makes obtaining 3D data relatively much easier.

3D face recognition is still faced with several challenges. One of these is the lack of an available benchmark dataset that could be used for experimentation and thus provide a clear and solid indication of the robustness of any recognition system. This is very clear if we knew that till 2003 the number of persons in datasets used for 3D face recognition experimentation didn't reach 100 [3]. In addition, very few papers deals with pose and expression variation [3], [4], [5].

Several other challenging could be listed regarding the progress and development of 3D face recognition systems

such as: Feature points allocation (this is still a debatable topic) that is also sensitive to the quality of data. Sampling density of the facial surface, and accuracy of the depth (e.g. no clear answer how much dense should a facial surface be? to accurately represent an individual face) [1]. No standard testing protocol is available to compare between different Face Recognition systems. Age factors, the size of the database, and efficiency of used algorithms are also considered as major challenges [3].

The rest of the paper is organized as follows: in the following section we will briefly review methodologies deployed in 3D Face Recognition systems. The next section, we will discuss our 3D image processing technique and our work on characterizing and allocating certain facial features automatically such as the tip of the nose, symmetry profile and cross-sectional profiles in the central region of the face. In addition, we will discuss our matching algorithm and the results, draw conclusion upon that and suggest future work for further improvement.

II. PREVIOUS WORK

Face recognition may be considered as a template matching with a high dimensionality. Dimensional reduction technique is often used to reduce dimensionality in order to reduce computation cost. Kirby used Principle Component Analysis (PCA) in addressing the problem [6]. Among many various algorithm PCA [7] has become a corner stone in 2D face recognition system. However 2D Face Recognition systems are unable to overcome the problems mentioned earlier.

Several approaches are used in the literature for 3D Face Recognition. Some of these are based on the segmentation of the face into meaningful points, lines and regions. Others are considered as model based approaches using information about texture, edges, and colors. Some techniques are considered as a profile-based techniques where multiple profiles comparisons are carried out, by which a set of profiles are compared against each other, such profiles might be symmetry ones, transverse, vertical or even cross-sectional [8]–[10].

Among the existing approaches for addressing 3D face recognition systems is the use of extended Gaussian Image

(EGI). Early work [11] by Lee segment convex regions in a range image based on the sing of the mean and Gaussian curvature, and create an extended Gaussian image. The matching algorithm is done by correlating the EGIs between the probe and an image in the gallery. The EGI in turn, describes the shape of an object by distribution of surface normal over the object structure.

Gokberk et al. [12] compare five approaches to 3D face recognition. They compare methods based on EGI, ICP matching, Range Profile, PCA, and Linear Discriminate Analysis LDA. The database they used was of 571 images from 160 people. They found out that ICP and LDA approaches offer the best performance, although performance is relatively similar among all approaches but PCA.

Gordon [13] segmented the face based on curvature description, then he extracted a set of features that describes both the curvature and metric size properties of the face. Thus each face becomes a point in the feature space, and the matching algorithm is done by nearest neighboring algorithm.

Nagamine [14] extracted five feature points and used it to standardize face pose, and then matching various curves or profiles though the face data. According to this experiment the best recognition rates were achieved using vertical profiles that pass through the central region of the face.

Achermann [15] approached 3D face recognition based on an extension of Hausdorff distance matching. 240 images were used, and 100% recognition rate was reported.

PCA were applied by [16] to address the problem of recognizing people based on 3D images. 37 different individual with 6 images /individual were used. Each image per subject has different facial expression.

In [17] 3D face recognition was approached by converting the 3D face data to an eigenform that is invariant to the type of shape deformation. The assumption is that the change of the geodesic distance due to facial expression is insignificant. Experiments are done using a database of 220 images of 30 persons and 100% recognition rate was reported. A total of 65 enrolment images were used for the 30 subject. "the use of more than one enrolment image per person will generally increase recognition rates, most unusual aspect of [17] work is the claim that it can distinguish between twins identical [3])".

Lee et all. [18] Approached the problem based on the curvature values at eight feature points on the face. Using support vector machine for classification they report a rank-one recognition rate 96% for a data set representing 100 persons. The feature points were manually allocated.

Profile-based appraoch was used by Zhang et. al. [10]. They first identify the symmetry plane of facial data. Then symmetry profile is computed, and then using mean curvature plot of the facial surface, and mean curvature plot of the symmetry profile three feature points are recognized.

The feature points on the nose define the Face Intrinsic Coordinate System FICS, all faces are aligned according to their FICS. For detection purposes the symmetry profile with another two transverse profiles provide a compact representation of the face called SFC face representations. For comparisons purposes SFC representations of faces are compared. 382 different scans database was used. EER for face authentication with variant facial expression reported was 10.8%. For scans with normal expressions .8% EER was reported. The symmetry profiles of two models to be compared are fist registered by mean of ICP algorithm. Then translation is done to make the cheek, forehead, and symmetry profiles coincide in the two models. The comparison is done by a set of sampling points on the corresponding profiles. Semiautomatic pre-processing procedure is used to trim of the non facial regions in the raw mesh. 166 individuals were used of which 32 individuals have multiple scans, and others have one scan.

III. Automatic Features Extraction

This section explains briefly our automatic approach for processing 3D images, localization of the symmetry profile and some feature points on the central region of the image, which are used in the following section for recognition purposes.

In our approach, our first goal is to automatically determine the symmetry profile along the face. This is undertaken by means of computing the intersection between the symmetry plane and the facial mesh, resulting in a planner curve that accurately represents the symmetry profile. Once the symmetry profile is successfully determined we compute a few feature points along the symmetry profile. These feature points are essential to compute other facial features, which can then be utilized to allocate the central region of the face and extract a set of profiles from that region.

In order to allocate the symmetry profile, we assume that it passes through the tip of the nose. This is in turn considered as the easiest feature point to recover and to allocate it we fit a bilinear blended Coon's surface patch. Coon's patch is simply parametric surface defined by a given four boundary curves [19]. Here, the four boundaries of the coon's patch are determined based on a boundary curve that encloses an approximated central region of interest, which is simply the region of the face that contains or likely to contain the nose area. This region is approximated based on the centre of the mass that represents the 3D facial image. It is important to stress out the point that the allocation of the central region of the face is a rough approximation that only aims to locate an area within the image that contains the nose.

Having the coon's surface generated as a reference to the points on the approximated central region, it becomes straight forward to recover initial estimation of the nose tip as the one with the maximum depth from the coon's patch. If we let V' denotes the set of all points that lie on the

scanned image within the approximated central region and let C denotes the set of points lying on the coon's surface patch (Figure1), then an initial approximation of the tip of the nose could be formulated as follows

$$NTIP_{init} = max\{d(p_i, e_j) : \forall p_i \in V', e_j \in C\} \quad (1)$$

Where $NTIP_{init}$ represents the tip of the nose initial estimation, $d(p_i, e_j)$ represents the Euclidean distance between the two points p_i, e_j and e_j is determined as

$$e_j = min\{d(p_i, e_j) : \forall e_j \in C\} \quad (2)$$

With the above formulation we simply establish a point correspondence between each point on the coon's surface patch and the nearest point to it on the facial image. Then, we choose the pair of points with the maximum distance as a candidate for being the tip of the nose.

Since the coon's surface is composed deliberately of relatively small number of points to keep the computation cost low, the above formulation gives an approximation to the tip of the nose. In order to give more accurate result we fit a plane within the coon's surface points that has been recovered using Equation (1) and recomputed that nose tip as the point with maximum depth value from the constructed plane (Figure 3).
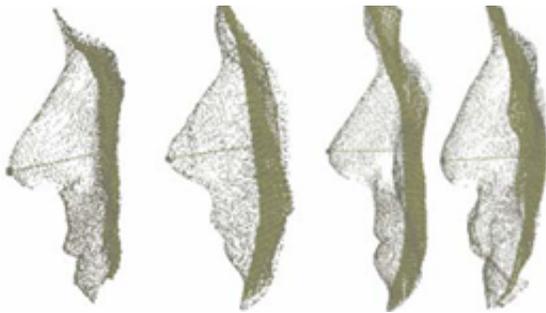

Figure 1. recovering the tip of nose by establishing points correspondence between the points on the approximated central region of the facial image and the bilinear coons patch.

Once the nose tip is recovered, we could further investigate the symmetry profile. The assumption made here, is that the symmetry profile passes through the nose tip and essentially has the shortest geodesic distance by comparisons with other profiles that lies on the facial image and passes through it too. Hence, constructing a plane along the facial image, extracting the profile that lies on the image and intersects the plane and work out its geodesic distance would recover the symmetry profile based on the above arrangements as shown in Figure 2.
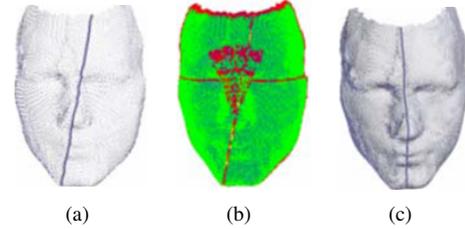

Figure 2.   Identifying symmetry plane (a) Initial identification of the symmetry profile (b) rotating and computing the geodesic distance of the profile (c) final result.

Having the symmetry profile and the tip of the nose identified, few other feature points are approximated based on simple local minima search criterion such as the lower part edge of the nose named NL, the point at the mid distance of the upper part of the symmetry profile named NM, the nose bridge denoted by NB and the NTIP represents the nose tip. These points are used for recognition purposes as shown in the following section. Figure 3 shows in details these points with the symmetry and eyes profile.
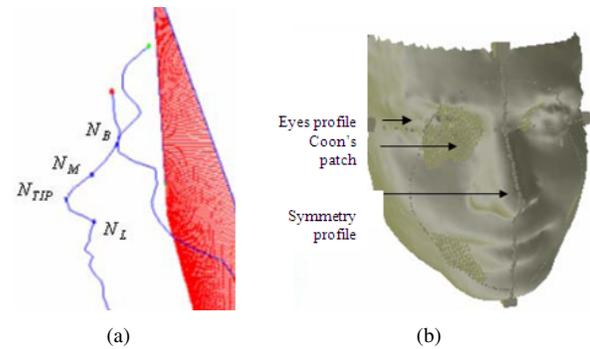

Figure 3.   Facial features identification (a) symmetry profile identification and analysis based on depth value to the reference depth plane (b) Eyes profile shown as the profile that passes through the nose bridge NB.

IV. DATA REGISTRATION

Scanned images can be of different poses within the Cartesian coordinate. Thus, in order to conduct matching between these different scans, the scanned images have to be properly aligned within the Cartesian coordinate. This process is carried out automatically by relying in the proposed algorithm discussed in the previous section. Three feature points namely the nose tip, Nose Bridge, and the lower edge of the nose are used to align the scanned image within the Cartesian product. It is important to stress out that the identification of these features points on the symmetry profile is an approximation, in other words, the allocated points may not be very precise. However they are good enough for matching and registration purposes as will be discussed and validated in the following section.

The alignment of the images is done by carrying out a rigid transformation of the dataset of the 3D points that make the image. The transformation is carried out based on the

symmetry profile and the nose tip and is composed of a series of simple translations and rotations to end up with an image aligned within the Cartesian coordinate with the nose tip residing at the origin and facing the positive Z-direction as shown in Figure 4.
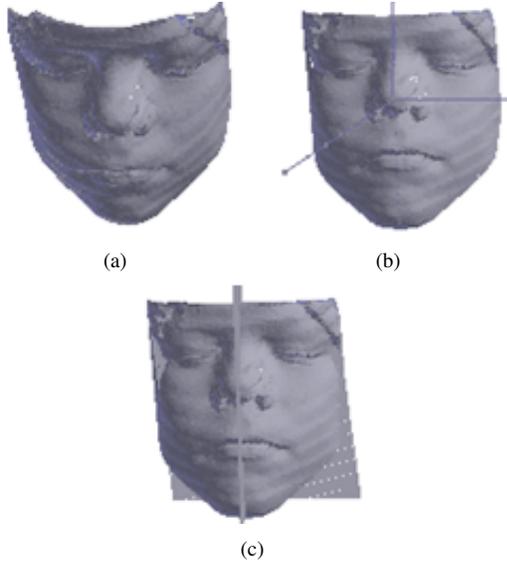

(a)   (b)

(c)

Figure 4.   processing and registering 3D images (a) loaded face in arbitrary pose and orientation (b) face is automatically processed and aligned with the Cartesian coordinate with the nose tip resides at the origin (c) the symmetry plane of the face.

V. MATCHING ALGORITHM

Some facial regions are considered more rigid and less sensitive to facial expression variation than others. Nose region for instance, is considered relatively rigid compared with other regions such as the mouth. For profile-based face recognition, the sensitivity of facial regions is even increasing and hence seriously affecting the recognition accuracy, because regions are represented by space profiles.

The lower part of the symmetry profile for example is highly sensitive to facial expression variations, while it is more rigid within the area bounded by NL and NB as shown in Figure 5.

Similarly, cross-sectional profiles that pass through the eyes area Figure(3 (b)) are highly sensitive to facial variations. Thus, it is not reliable to use it for recognition purposes.

So for our recognition matching algorithm we use the central part of the symmetry profile which lies on the nose region (Figure 5) and central part of the cheeks profile. The cheeks profile is simply the profile that crosses the nose area at the mid distance between the points NB and NL.

In order to minimize the input data, we compute the Fourier coefficients of the designated profiles and store it in a database, other than storing the actual points of the profile. Thus, having a database of images representing different

individuals where each person is represented by two profiles stored by means of their Fourier's.
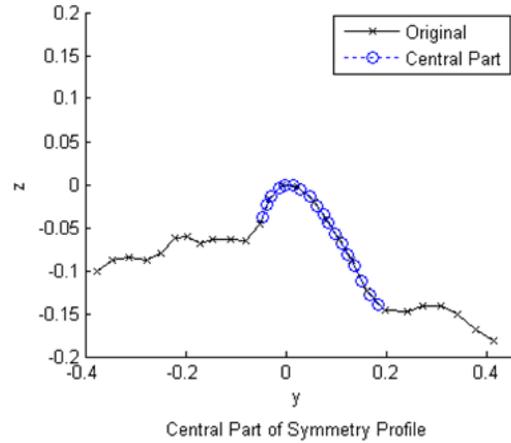

Central Part of Symmetry Profile

Figure 5.   Central part of the symmetry profile

On real time the database file would be loaded into memory and the profiles would be reconstructed according to the general form of Fourier series expansion Equation (1)

$$f(t) = \frac{1}{2}a_0 + \sum_{n=1}^{m} a_n \cos(nt) + b_n sin(nt) \qquad (3)$$

M is chosen to be relatively small, such that the number of coefficients required to reconstruct the curve is relatively much smaller than the number of 3D points that represent the profile. Matching faces against each other is carried out by a profile-by-profile comparisons with closest match selected. The comparison of the profiles is done point by point on the 3D space similar to [10]. If we let L_p and L_g be two profiles representing the central part of the symmetry profile of a probe and an image in the gallery 'database' respectively (Figure 6).
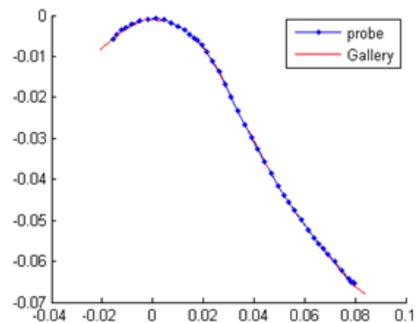

Figure 6.   Profile-based comparisons

The distance between the two polylines is directional, in other words the mean distance between the two profiles L_p

and L_g is not necessarily the same as the distance from L_g to L_p. These distances are defined as

$$d_{pg} = \frac{1}{n} \sum_{p_1 \in L_p} min_{p_2 \in L_g} d(p_1, p_2) \qquad (4)$$

$$d_{gp} = \frac{1}{m} \sum_{p_2 \in L_g} min_{p_1 \in L_p} d(p_2, p_1) \qquad (5)$$

Where n and m represent the number of positions points on the profiles L_p and L_g and $d(p_1, p_2)$ is the Euclidean distance between p_1 and p_1. Thus, the similarity measure between the two profiles can be formulated as

$$E = \frac{1}{2}(d_{pg} + d_{gp}) \qquad (6)$$

where the measure between the two images is computed as

$$E_{total} = E_{cs} + E_{cc} \qquad (7)$$

where the E_{cs} represents the similarity measure between the central parts of the symmetry profiles and the E_{cc} represents the similarity between the central part of the cheeks profiles of two images.

VI. EXPERIMENTS AND RESULTS

For experimental purposes a 3D platform has been developed using Microsoft Foundation Classes (MFC), c++ and openGL. The platform is used to load 3D images, carry out the features extraction and conduct the matching algorithm to search for the best match in Database.
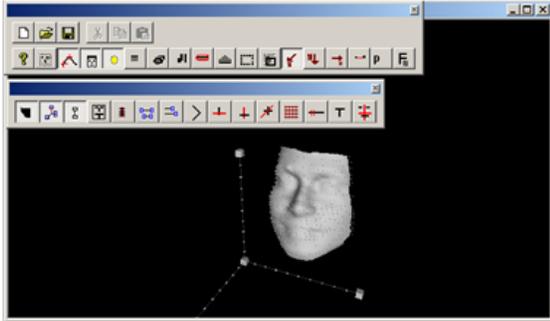

Figure 7.   3D Environment for loading, processing and recognizing 3D images of human faces

In testing our processing and matching algorithm two experiments were carried out using two different databases. In the first experiment a database representing 22 different individuals was used. Each individual in the database is represented by 5 images each represent a different pose (Figure 8. Only one profile was used to for comparing images, namely the central part of the symmetry profile.

Figure 9 shows a screen shot for the database file that we used in our experimentation. In this experiment the first line in the file represents the number of images in

the database. Individual images are numbered as 1, 2, , 22 and each number is followed by the Fourier coefficients representing the central profiles of that person. Hence, in a recognition transaction, an image is loaded into our system, its features are extracted, the pose is aligned within the Cartesian coordinate and finally the database file is loaded into memory and profiles are constructed and compared against the image.

Figure 8.   3D facial scan images representing 4 different poses (a) +30 degree around the y-axis (b) rotated by 30 degree around the z-axis (c) rotated by -30 degree around the y-axis (d) rotated by -30 degree around the x-axis and (e) aligned within the Cartesian coordinate with the nose tip residing at the origin as detailed in section 4.

In this particular experiment 100% recognition rate was achieved. This result was expected as the main face variation is due to the pose not to the facial expression variation. In the second experiment we used gavaBDB [20] which is a public 3D database of human faces. The database covers enough systematic variation in terms of facial poses and facial expressions. Total number of people images enrolled in the database is 60, 45 out of these represent males and 15 represents female. Each individual in the database is represented by 9 different images. In our experiment we only consider 7 images per person and discarded two images/ person from the database as only part of the face is available in the image (e.g. left side or right side of the face is in the image only).

Figure 9.   Database file that stores the Fourier coefficients of profiles representing different individuals.

Both profiles (central parts of cheeks and symmetry) are used in this experiment as shown in Figure 10. In total 365 images were tested using our algorithm and were correctly identified which corresponds to an accuracy recognition rate equal to 86.90%. Inaccurate results were due to the failure of the feature extractions algorithm to standardize the pose and hence extracting the required profiles for comparing

the images. In other words 55 different images that were incorrectly identified were actually falsely rejected by the matching algorithm. This raises the False Rejection Rate (FRR) of this experiment to 13.0% which is due to the inaccurately identified features which result in relatively large error value between the profiles of the compared images and result in rejecting the image.
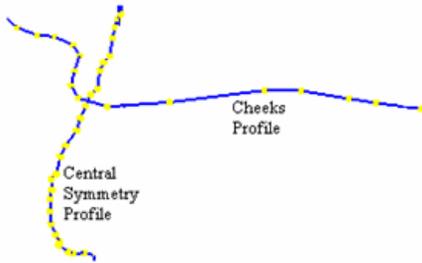

Figure 10. profiles used to compute similarity measure between images.

VII. Conclusion and Future Work

In this paper we introduced a new technique for processing 3D images of human faces and extract certain features to be used for recognition purposes. In addition, we have successfully demonstrated that utilizing rigid regions of a human face is very useful in terms of improving recognition rates and minimizing the search space. The average processing time for recognition transaction was 10 seconds. This time includes, loading an image, processing it, extract facial features, standardize the pose, load the database file and conduct the profile comparisons.

Possible improvement to the current recognition system would include improving the features extraction algorithm so that more features points are extracted automatically. In addition, the algorithm should be improved to deal with low quality images. In our experiments the algorithm failed when the images contains holes or spikes, simply because this would lead to false identification of the tip of the nose and would essentially lead to false identification of the rest of the features required.

Improving the features extraction algorithm and enhance it to recover more features points would necessarily improve the recognition rate, specially that recovering more features points would allow us to derive some metric measurements from the image that may be used for comparisons between images next to the profile based comparisons.

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