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3D Face Recognition Using Geodesic Facial Curves to Handle Expression, Occlusion and Pose Variations

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***Abstract*—this paper illustrates the use of radial facial curves on 3D meshes to mode facial deformation caused by expression, occlusion and variation in poses and to recognize faces despite large expression, in presence of occlusion and pose variations. Here we represent facial surface by indexed collection of radial geodesic curves on 3D face meshes emanating from nose tip to the boundary of mesh and compare the facial shapes by comparing shapes of their corresponding curves. We use elastic shape analysis for comparing shapes of facial curves because elastic matching seems natural for facial deformation and is robust to challenges such as large facial expressions (especially those with open mouths), large pose variations, missing parts, and partial occlusions due to glasses, hair, and so on. Our results match or improve upon the state-of-the-art methods on two prominent databases:,GavabDB, and Bosphorus, each posing a different type of challenges.**

***Index Terms*—biometrics, 3D face recognition, data restoration, geodesic curve, occlusion detection, shape analysis, and removal, quality control etc.**

I. INTRODUCTION

Face is the natural assertion of identity: We show our face as proof of who we are. Due to this widely accepted cultural convention, face is the most widely accepted biometric modality. From last few decades a biometric-based recognition system becoming very useful in a variety of applications. While some biometric recognition systems, such as fingerprints and iris, have already reached very high level of accuracy, but they have a limited use in non-cooperative scenarios. On the other hand, the less-intrusive modalities like the face and gait have not reached the desired levels of accuracy. Over the past three decades, the techniques for face recognition have received a growing attention within the computer vision community.

Automated human face recognition has numerous applications in variety of fields including automated secured access to ATM machines and buildings, automatic surveillance, forensic analysis, fast retrieval of records from databases in police departments, automatic identification of patients in hospitals, checking for fraud or identity theft, and human-computer interaction.

Considerable research attention has been directed, over the past few decades, towards developing reliable automatic face recognition systems that use two dimensional (2D) facial images. Commercial systems are also now available for 2D face recognition. Two dimensional face recognition systems are inadequate for robust face recognition as 2D color imaging in that nuisance variables, such as illumination and small pose changes, have a relatively greater influence on the observations. Three dimensional (3D) face recognition technologies is now emerging, in part, due to the availability of improved 3D imaging devices and processing algorithms. For such techniques, 3D images of the facial surface are acquired using 3D acquisition devices and are used for recognition purposes. Three dimensional facial images have some advantages over 2D facial images. Their pose can be easily corrected by rigid rotations in 3D space. The shape of a 3D facial surface depends on its underlying anatomical structure. Hence, images acquired using 3D laser range finders are invariant to illumination conditions during image acquisition. 3 dimensional facial images also provide structural information about the face (e.g., surface curvature and geodesic distances), which cannot be obtained from a single 2D image. However, 3D scans often suffer from the problem of missing parts due to self-occlusions or external occlusions or some imperfections in the scanning technology. Additionally, variations in face scans due to changes in facial expressions can also degrade face recognition performance. To be useful in real-world applications, a 3D face recognition approach should be able to handle these challenges, i.e., it should recognize people despite large facial expression, occlusion and pose variations.

Additionally, we provide some basic tools for statistical shape analysis of facial surfaces. These tools help us to compute a typical or average shape and measure the intraclass variability of shapes, and will even lead to face atlases.

II. LITERATURE SURVEY

The task of recognizing 3D face scans has been approached in many ways, leading to varying levels of successes. We refer the reader to one of many extensive surveys on the topic:

A. Deformable template based approaches.

Several 3D face recognition approaches in recent years rely on deforming facial surfaces into one another, under some chosen criteria, and use quantifications of these deformations as metrics for face recognition. Among these, the ones using nonlinear deformations facilitate local stretching, compression, and bending of surfaces to match each other and are referred to as elastic methods. For instance, Kakadiaris et al. [3] utilize an annotated face model to study geometrical variability across faces. The annotated face model is deformed elastically to fit each face, thus matching different anatomical areas such as the nose, eyes, and mouth.

B. Facial Symmetry Approaches

In [4], Passalis et al. use automatic landmarking to estimate the pose and to detect occluded areas. The facial symmetry is used to overcome the challenges of missing data here. Similar approaches, but using manually annotated models, are presented in [5] and [6]. For example, Lu and Jain [6] use manual landmarks to develop a thin-plate-spline-based matching of facial surfaces. A strong limitation of these approaches is that the extraction of fiducial landmarks needed during learning is either manual or semi-automated, except in [4], where it is fully automated.

The uncontrolled conditions of real-world biometric applications pose a great challenge to any face recognition approach. The unconstrained acquisition of data from uncooperative subjects may result in facial scans with significant pose variations along the yaw axis. Such pose variations can cause extensive occlusions resulting in missing data. In this paper, a novel 3D face recognition method is proposed that uses facial symmetry to handle pose variation. It employs an automatic landmark detector that estimates pose and detects occluded areas for each facial scan. Subsequently, an Annotated Face Model is registered and fitted to the scan. During fitting, facial symmetry is used to overcome the challenges of missing data. Unlike existing methods that require frontal scans, this method performs comparisons among interpose scans using a wavelet-based biometric signature. It is suitable for real-world applications as it only requires half of the face to be visible to the sensor. This method was evaluated using databases from the University of Notre Dame and the University of Houston that, to the best of our knowledge, include the most challenging pose variations publicly available. In these databases the average rank-one recognition rate of the proposed method was 83:7 %

C. Local regions/features approach.

Another common framework especially for handling expression variability is based on matching only parts or regions rather than matching full faces. Lee et al. [7] use ratios of distances and angles between eight fiducial points, followed by an SVM classifier. Similarly, Gupta et al. [8] use euclidean/geodesic distances between anthropometric fiducial points in conjunction with linear classifiers. As stated earlier, the problem of automated detection of fiducial points is nontrivial and hinders automation of these methods. Gordon [9] argues that curvature descriptors have the potential for higher accuracy in describing surface features and are better suited to describing the properties of faces in areas such as the cheeks, forehead, and chin. These descriptors are also invariant to viewing angles. Li et al. [10] design a feature pooling and ranking scheme to collect various types of low-level geometric features, such as curvatures, and rank them according to their sensitivity to facial expressions. Along similar lines, Wang et al. [1] use a signed shape-difference map between two aligned 3D faces as an intermediate representation for shape comparison. McKeon and Russ [12] use a region ensemble approach that is based on Fisherfaces, i.e., face representations are learned using Fisher's discriminate analysis. In [12], Huang et al. use a multistage local binary pattern for a 3D face jointly with shape index. Similarly, Moorthy et al. [13] use Gabor features around automatically detected fiducial points. To avoid passing over deformable parts of faces encompassing discriminative information, Faltemier et al. [14] use 38 face regions that densely cover the face, and fuse scores and decisions after performing ICP on each region. Queirolo et al. [15] use surface interpenetration measure as a similarity measure to match two face images. The authentication score is obtained by combining the SIM values corresponding to the matching of four different face regions: circular and elliptical areas around the nose, forehead, and the entire face region. Alyuz et al. use average region models (ARMs) locally to handle the challenges of missing data and expression-related deformations. They manually divide the facial area into several meaningful components and the registration of faces is carried out by separate dense alignments to the corresponding ARMs. A strong limitation of this approach is the need for manual segmentation of a face into parts that can then be analyzed separately.

D. Surface distance-based approaches.

There are several papers that utilize distances between points on facial surfaces to define features that are eventually used in recognition. (Some papers call it geodesic distance but, to distinguish it from our later use of geodesics on shape spaces of curves and surfaces, we shall call it surface distance.) These papers assume that surface distances are relatively invariant to small changes in facial expressions and therefore help generate features that are robust to facial expressions. Bronstein et al. [16] provide a limited experimental illustration of this invariance by comparing changes in surface distances with the euclidean distances between corresponding points on a canonical face surface. To handle the open mouth problem, they first detect and remove the lip region, and then compute the surface distance in the presence of a hole corresponding to the removed part. The assumption of preservation of surface distances under facial expressions motivates several authors to define distance-based features for facial recognition. Samir et al. [17] use the level curves of the surface distance function (from the tip of the nose) as features for face recognition. Since an open mouth affects the shape of some level curves, this method is not able to handle the problem of missing data due to occlusion or pose variations. A similar polar parameterization of the facial surface is proposed in [18], where the authors study local geometric attributes under this parameterization. To deal with the open mouth problem, they modify the parameterization by disconnecting the top and bottom lips. The main limitation of this approach is the need for detecting the lips, it use surface distances to define facial stripes which, in turn, are used as nodes in a graph-based recognition algorithm. The main limitation of these approaches, apart from the issues resulting from open mouths, is that they assume that surface distances between facial points are preserved within face classes. This is not valid in the case of large expressions. Actually, face expressions result from the stretching or the shrinking of underlying muscles and, consequently, the facial skin is deformed in a nonisometric manner. In other words, facial surfaces are also stretched or compressed locally, beyond a simple bending of parts.

III. EXISTING SYSTEM

In the previous section we reviewed the existing systems for the 3D face recognition.The main limitations of these approaches for 3D face recognition are,

1. These approaches do not deal with issue of open mouth.
2. A part from the issues resulting from open mouths, is that they assume that surface distances between facial points are preserved within face classes. This is not valid in the case of large expressions. Actually, face expressions result from the of elastic shape analysis in 3D face recognition.
3. Some of these approaches has been directed toward tackling changes in facial expressions while only a relatively modest effort has been spent on handling occlusions and missing parts. Although a few approaches and corresponding results dealing with missing parts have been presented, none, to our knowledge, has been applied systematically to a full real database containing scans with missing parts.

IV. PROPOSED SYSTEM

In this paper, we present a framework for analyzing facial shapes, in the process dealing with large expressions, occlusions, and missing parts. Additionally, we provide some basic tools for statistical shape analysis of facial surfaces. These tools help us to compute a typical or average shape and measure the intraclass variability of shapes, and will even lead to face atlases in the future.
The main objectives of this research are:

i) To extracts, analyzes, and compares the shapes of radial curves of facial surfaces.
ii) To develops an elastic shape analysis of 3D faces by extending the elastic shape analysis of curves [2] to 3D facial surfaces.
iii) To develop an occlusion detection and removal step that is based on recursive-ICP to handle occlusions.
iv) To introduce a restoration step that uses statistical estimation on shape manifolds of curves to handle the missing data. Specifically, by using PCA on tangent spaces of the shape manifold to model the normal curves and use that model to complete the partially observed curves.
v) To automatically detect nose tip of face image

Here we use the geodesic radial curve emanating from the nose tip to the boundary of mesh in different direction as a metrics for comparing face. The faces can be compared by comparing their corresponding curves. We use elastic matching of radial curves to model the deformation caused by large facial expression.Fig.1 illustrates the flowchart for proposed 3D face recognition system.

First of all, the probe P and the gallery G meshes are preprocessed. This step is essential to improve the quality of raw images and to extract the useful part of the face. It consists of a Laplacian smoothing filter to reduce the acquisition noise, a filling hole filter that identifies and fills holes in input mesh, and a cropping filter that cuts and returns the part of the input mesh inside of a specified sphere. Then, a course alignment is performed based on the translation vector formed by the tips of the noses. This step is followed by a finer alignment based on the well-known ICP algorithm in order to find whether there is occlusion and to remove the occluded part if present. Next, we extract the radial geodesic curves emanating from the nose tip and having different directions on the face. next, a quality control module inspects the quality of each curve on both meshes and keeps only the good ones based on defined criteria. In next step the missing curves due to occlusion are restored.

In order to improve matching and comparisons between the extracted curves, we advocate the use of elastic matching. Actually, facial deformations dues to expressions can be attenuated by an elastic matching between facial curves. Hence, we obtain algorithm for computing geodesics between pair wise of radial curves on gallery and probe meshes. The length of one geodesic measures the degree of similarity between one pair of curves. The fusion of the scores on good quality common curves, produced similarity score between the faces P and G. Based on that score the faces will be recognized.

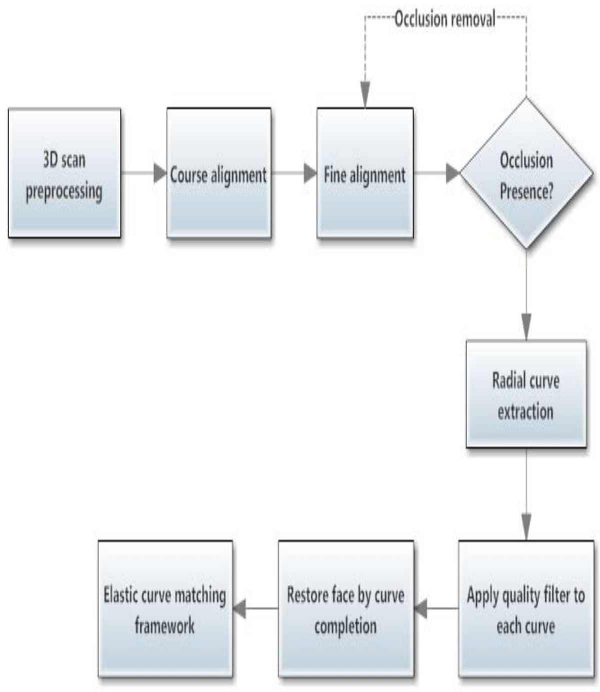

Fig.1 flowchart of proposed system

V. CONCLUSION

As 3D face scans suffers from the challenges like large expression, presence of occlusions or pose variations. To handle these challenges in face recognition, we proposed novel geometric framework for analyzing, comparing and matching 3D faces. We select curves on faces as feature for proposed system and use elastic matching of radial curves in order to handle deformation of face caused by large facial expression.

We also proposed occlusion detection and removal step base on recursive ICP to deal with occluded scans along with curve restoration steps.

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