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3D Face Recognition under Expressions, Occlusions, and Pose Variations

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Abstract: We propose framework for analysing 3D faces, with the specific goals of comparing, matching, and averaging their shapes. Here we represent facial surfaces by radial curves emanating from the nose tips shape analysis. Here we detect facial deformations and large facial expressions large pose variations, missing parts, and partial occlusions due to glasses, hair, and illustrates the use of radial facial curves on 3D meshes. 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 eyes and compare the facial shapes by comparing shapes of their corresponding curves. Here we using MATLAB for implementing our project.

Keywords: Occlusion- Blockage due to which image can not be properly seen. Pose Variation- Different views of the same image. Euclidean Distance- Distance between two points in Euclidean space. Face Recognition - a type of biometric software application that can identify a specific individual in a digital image by analysing and comparing patterns.

I. INTRODUCTION

Face is the main identity to show proof of yourself. Face is widely accepted cultural convention, and most widely accepted biometric modality. Biometric based recognition systems have became very useful in last decades in a lot 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, face has not reached to that much of accuracy. Now a days it is growing rapidly and automated human face recognition has enormous applications in a lot 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 aimed, over the past few decades, towards developing trustable automatic face recognition systems that use two dimensional (2D) facial images. Three dimensional (3D) face recognition technologies are now becoming prominent in part, due to the availability of enhanced 3D imaging devices and processing algorithms. For techniques as such, 3D images of the facial surface are acquired using 3D acquisition devices and are used for recognition purposes. Three dimensional facial images have some benefits over 2D facial images. Their pose can be easily corrected by rigid rotations in 3D space. 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. Three dimensional facial images provide structural information about the face (e.g., surface curvature and geodesic distances), which cannot be acquired from a single 2D image. Additionally, variations in face scans.

Changes in facial expression scan degrade face recognition performance. For being 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. A few approaches and corresponding results dealing with missing parts have been presented. In this paper, we present a comprehensive Riemannian framework to analyse 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 to compute a typical or average shape and measure the intra class variability of shapes, and will even lead to face atlases in the future. Advances in sensing technology and the availability of sufficient computing power have made 3D face recognition one of the attractive modalities for biometrics. 3D registration remains the crucial part in the recognition chain as in 2D. As most existing registration approaches require landmarks (feature points) to be located on the surface as initialization, a robust estimation of facial feature points is of prime importance. 3D methods are found to be more robust under changing illumination conditions [2]. In 3D, the prominence of the nose makes it a relatively easy candidate for fast, heuristic-based approaches [3]. For instance in [4] a coarse to-fine heuristic procedure is described to locate tip of the nose, and subsequent pose correction depends on this point. D'Hose et al. use Gabor filter responses and ICP to find tip of the nose, and use it to restrict the search for other landmarks [5]. In [6], nose is located first, and candidates for the left over landmark points are encoded according to their position with respect to the nose. Even though relying on a single landmark is a potential threat to the robustness of the system, nose localization can produce great results in practice, since nose is the easiest landmark to locate and has the best effect in registration [7].Apart from the nose , eye and mouth corners are the most generally used facial landmarks. If the facial symmetry axis can be found, locating the eye and mouth corners is straight forward and very easy for neutral faces [8]. However, the search for the symmetry axis can be costly without the guiding landmarks. Curvature-based features are promising in 3D, but they suffer from a number of problems [9], [10]. Reliable estimation of curvature requires a strong pre-processing that eliminates surface irregularities, especially near eye and mouth corners. Two problems are associated with this pre-processing: The computation is expensive, and the smoothing destroys local feature information to a great length, producing many points with similar curvature values in each local neighbourhood. However, curvature can be used to greatly reduce the area for the more costly fine-tuned search. For flat-nosed persons, the “tip of the nose” is not a point, but a whole area of points with similar curvature. This is the natural version of the smooth-areas problem artificially created with pre-processing. More elaborate 3D methods, like spin images, are very costly in practice, but may become feasible with fast embedded hardware or with sufficient down sampling [11]. Recently, Kakadiaris et al. proposed matching of spin images to align faces prior to ICP, and obtained very good results [12]. The reported time delay to convert raw scanner data to registered metadata is only 15seconds.

II. RELATED WORK

There are various approaches that help in face recognition. We refer the reader to one of many extensive surveys on the topic:

A. Deformable template based approaches.

Many 3D face recognition approaches in late 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 the 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 nose, eyes, and mouth.

B. Facial Symmetry Approaches

In [4], Passalis et al. use the automatic landmarking to estimate the pose and to detect occluded areas. The missing data is found by using facial symmetry. Same 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 major drawback 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 threat 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 of the data. In the paper, a novel 3D face recognition method is presented that uses facial symmetry to handle pose variation. It employs an automatic landmark detector that estimates the pose and detects the 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 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 Fisher faces, 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. use Gabor features around automatically detected fiducial points. To avoid passing over deformable parts of faces encompassing discriminative information, Faltemier et al.

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use 38 face regions that densely cover the face, and fuse scores and decisions after performing ICP on each region. Queirolo et al. 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 many papers that utilize distances between points on facial surfaces to define the features that are eventually used in recognition. These papers assume that the surface distances are relatively invariant to small changes in the facial expressions and therefore help generate features that are robust to facial expressions. Bronstein et al. 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 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. 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, 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 no isometric manner. In other words, facial surfaces are also compressed or stretched locally, beyond a simple bending of parts.

III. PROPOSED SYSTEM

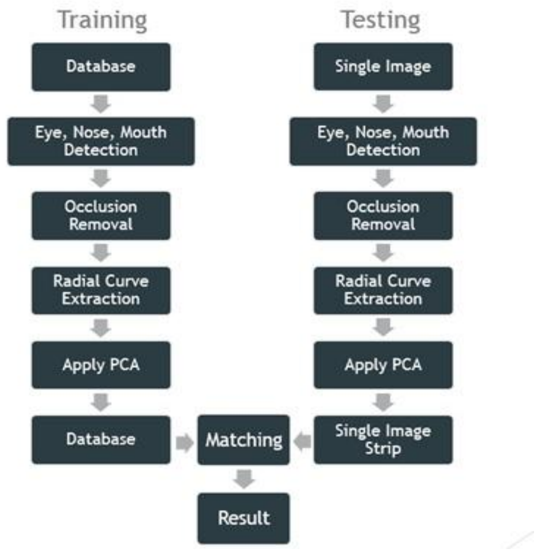

Fig .1 Block Diagram of Proposed System

Algorithm for the system-

PCA Algorithm:

In our system we are using PCA algorithm for detection of the face. In the PCA algorithm we are using radial curve extraction, here we first detect nose tip to recognize the face.

The main objectives of this research are:

(i) To extract, analyse, and compare 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 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 flowchart for proposed 3D face recognition system.

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

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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.

IV. KEY FEATURES

1. High-level language for technical computing
2. Development environment for managing code, files, and data
3. Interactive tools for iterative exploration, design, and problem solving
4. Mathematical functions for linear algebra, statistics, Fourier analysis, filtering, optimization, and numerical integration.

V. CONCLUSION

As 3D face scans suffers from the challenges like large expressions, presence of occlusions or pose variations. To handle these challenges in face recognition, we proposed novel geometric framework for analysing, comparing and matching 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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