Paper Title

3D Face Recognition based on Geodesic Distances

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Principal Author's Biography
Shalini Gupta received a BE degree in Electronics and Electrical Communication Engineering from Punjab Engineering College, India. She received a MS degree in Electrical and Computer Engineering from the University of Texas at Austin, where she is currently a PhD student. During her masters, she developed techniques for computer aided diagnosis of breast cancer. She is currently investigating techniques for 3D human face recognition.

Keywords
Geodesic distances, three-dimensional face recognition, range image, biometrics

Extended Abstract

Problem Statement:

Automated human identification is required in applications such as access control, passenger screening, passport control, surveillance, criminal justice and human computer interaction. Face recognition is one of the most widely investigated biometric techniques for human identification. Face recognition systems require less user co-operation than systems based on other biometrics (*e.g.* fingerprints and iris). Although considerable progress has been made on face recognition systems based on two dimensional (2D) intensity images, they are inadequate for robust face recognition. Their performance is reported to decrease significantly with varying facial pose and illumination conditions [1]. Three-dimensional face recognition systems are less sensitive to changes in ambient illumination conditions than 2D systems [2]. Three-dimensional face models can also be rigidly transformed to a canonical pose. Hence, considerable research attention is now being directed toward developing 3D face recognition systems.

Review of Previous Work:

Techniques employed for 3D face recognition include those based upon global appearance of face range images, surface matching, and local facial geometric features. Techniques based on global appearance of face range images are straight-forward extensions of statistical learning techniques that were successful to a degree with 2D face images. They involve statistical learning of the 3D face space through an ensemble of range images. A popular 3D face recognition technique is based on principal component analysis (PCA) [3] and is often taken as the baseline for assessing the performance of other algorithms [4]. While appearance based techniques have met with a degree of success, it is intuitively less obvious exactly what discriminatory information about faces they encode. Furthermore, since they employ information from large range image regions, their recognition performance is affected by changes in facial pose, expression, occlusions, and holes.

Techniques based on surface matching use an iterative procedures to rigidly align two face surfaces as closely as possible [5]. A metric quantifies the difference between the two face surfaces after alignment, and this is employed for recognition.The computational load of such techniques can be considerable, especially when searching large 3D face databases. Their performance is also affected by changes in facial expression.

For techniques based on local geometric facial features, characteristics of localized regions of the face surface, and their relationships to others, are quantified and employed as features. Some local geometric features that have been used previously for face recognition include surface curvatures, Euclidean distances and angles between fiducial points on the face [6, 7, 8], point signatures [9], and shape variations of facial sub regions [10]. Techniques based on local features require an additional step of localization and segmentation of specific regions of the face. A pragmatic issue affecting the success of these techniques is the choice of local regions and fiducial points. Ideally the choice of such regions should be based on an understanding of the variability of different parts of the face within and between individuals.

Three dimensional face recognition techniques based on local feature have been shown to be robust to a degree to varying facial expression [9]. Recently, methods for expression invariant 3D face recognition have been proposed [11]. They are based on the assumption that different facial expressions can be regarded as isometric deformations of the face surface. These deformations preserve intrinsic properties of the surface, one of which is the geodesic distance between a pair of points on the surface.

Based on these ideas we present a preliminary study aimed at investigating the effectiveness of using geodesic distances between all pairs of 25 fiducial points on the face as features for face recognition. To the best of our knowledge, this is the first study of its kind. Another contribution of this study is that instead of choosing a random set of points on the face surface, we considered facial landmarks relevant to measuring anthropometric facial proportions employed widely in facial plastic surgery and art [12]. The performance of the proposed face recognition algorithm was compared against other established algorithms.

Proposed Approach:

Three dimensional face models for the study were acquired by an MU-2 stereo imaging system by 3Q Technologies Ltd. (Atlanta, GA). The system simultaneously acquires both shape and texture information. The data set contained 1128 head models of 105 subjects. It was partitioned into a gallery set containing one image each of the 105 subjects with a neutral expression. The probe set contained another 663 images of the gallery subjects with a neutral or an arbitrary expression. The probe set had a variable number of images per subject (1-55).

Models were rigidly aligned to frontal orientation and range images were constructed. They were median filtered and interpolated to remove holes. Twenty-five fiducial points, as depicted in Figure 1 were manually located on each face. Three face recognition algorithms were implemented. The first employed 300 geodesic distances (between all pairs of fiducial points) as features for recognition. The fast marching algorithm for front propagation was employed to calculate the geodesic distance between pairs of points [13]. The second algorithm employed 300 Euclidean distances between all pairs of fiducial points as features. The normalized L1 norm where each dimension was divided by its variance, was used as the metric for matching faces with both the Euclidean distance and geodesic distance features.

The third 3D face recognition algorithm implemented was based on PCA. For this algorithm, a subsection of each face range image of size 354 pixels, enclosing the main facial features was employed. The gallery and probe sets employed to test the performance of this algorithm were the same as those used in the first and second algorithms. Additionally a separate set of 360 range images of 12 subjects (30 images per subjects), was used to train the PCA classifier. Face range images were projected on to 42 eigen vectors accounting for 99% of the variance in the data. Again, the L1 norm was employed for matching faces in the 42 dimensional PCA sub space.

Verification performance of all algorithms was evaluated using the receiver operating characteristic (ROC) methodology, from which the equal error rates (EER) were noted. Identification performance was evaluated by means of the cumulative match characteristic curves (CMC) and the rank 1 recognition rates (RR) were observed. The performance of each technique for the entire probe set, for neutral probes only and for expressive probes only were evaluated separately.

Experimental Results:

Table 1 presents the equal error rates for verification performance and the rank 1 recognition rates for identification performance of the three face recognition algorithms. Figure 2(a) presents ROC curves of the three systems for neutral expression probes only. Figure 2(b) presents the CMC curves for the three systems for neutral expression probes only. It is evident that the two algorithms based on Euclidean or geodesic distances between anthropometric facial landmarks ($EER \sim 5\%$, $RR \sim 89\%$) performed substantially better than the baseline PCA algorithm ($EER = 16.5\%$, $RR = 69.7\%$). The algorithms based on geodesic distance features performed on a par with the algorithm based on Euclidean distance features. Both were effective, to a degree, at recognizing 3D faces. In this study the performance of the proposed algorithm based on geodesic distances between anthropometric facial landmarks decreased when probes with arbitrary facial expressions were matched against a gallery of neutral expression 3D faces. This suggests that geodesic distances between pairs of landmarks on a face may not be preserved when the facial expression changes. This was contradictory to Bronstein *et al.*'s assumption regarding facial expressions being isometric deformations of facial surfaces [11].

In conclusion, geodesic distances between anthropometric landmarks were observed to be effective features for recognizing 3D faces, however they were not more effective than Euclidean distances between the same landmarks. The 3D face recognition algorithm based on geodesic distance features was affected by changes in facial expression. In the future, we plan to investigate methods for reducing the dimensionality of the proposed algorithm and to identify the more discriminatory geodesic distance features.

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Figures and Tables:

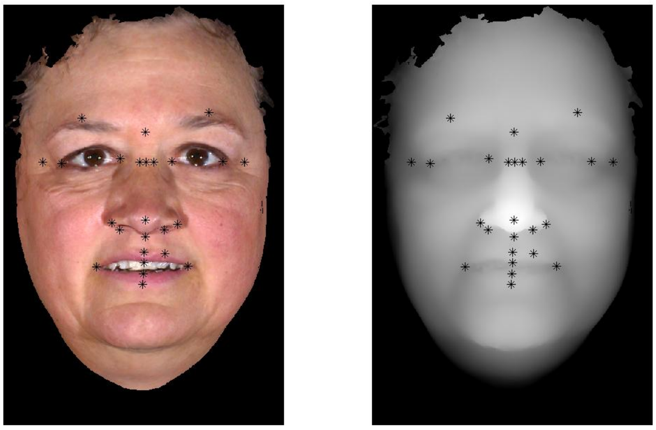
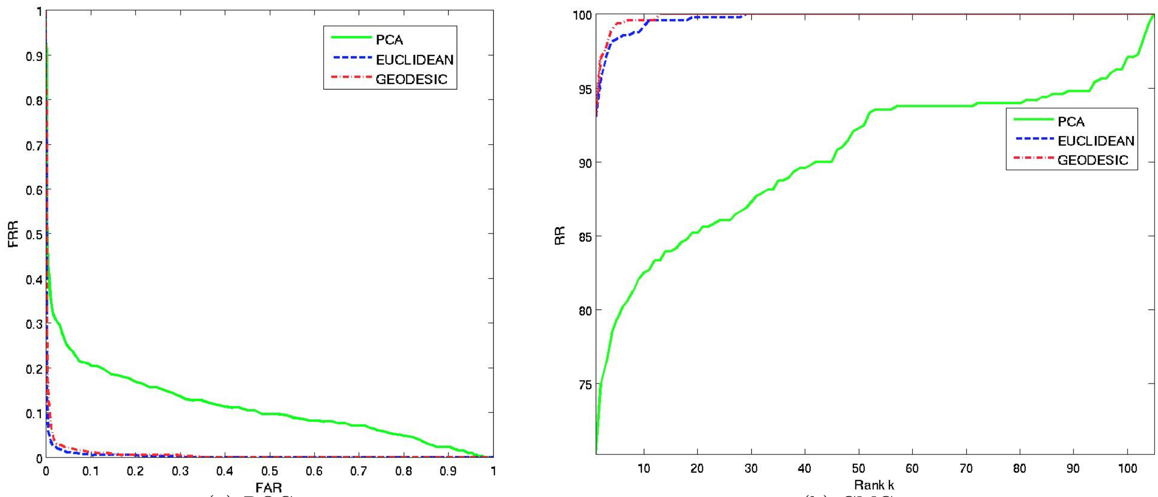


Figure 1: The figures show the 25 anthropometric landmarks that were considered on a color and range image of a human face.



(a) ROC (b) CMC

Figure 2: This figure presents the 2(a) verification performance in terms of an ROC curve; 2(b) the cumulative match characteristic curves for the identification performance of the three face recognition algorithms with the neutral expression probes only.

Method	EER (%)			Rank 1 RR (%)		
	N-N	N-E	N-All	N-N	N-E	N-All
GEODESIC	2.7	8.5	5.6	93.1	81.4	89.9
EUCLIDEAN	2.2	6.7	4.1	92.9	78.1	88.8
PCA	18.1	13.4	16.5	70.2	68.3	69.7

Table 1: Verification and identification performance statistics for the face recognition systems based on PCA, Euclidean distances and geodesic distances. N-N represents performance of a system for the neutral probes only, N-E for the expressive probes only and N-All for all probes.

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