A Survey of Approaches for Curve Based Facial Surface Representations For Three-Dimensional Face Recognition

Aouragh Salima[1,3], Sbaa Salim[2], Taleb-Ahmed Abdelmalik[3]
[1] Department of Electrical engineering, Kasdi Merbah University, Ouargla, Algeria.
[2] Department of Electrical engineering, Mohamed Kheider University, Biskra, Algeria.
[3] LAMIH UMR CNRS 8201 UVHC, University of Valenciennes and Hainaut Cambrésis, France.
aouragh.salima@gmail.com, s.sbaa@univ-biskra.dz, taleb@univ-valenciennes.fr

Abstract

The majority of face recognition methods using three-dimensional data, either alone or in combination with two-dimensional intensity images are covered in existing survey papers. General 3D face representation has been extensively studied and various approaches have been proposed in the literature. This overview focuses on the class of researches exploiting curve concept to represent facial surface for three-dimensional face recognition using profile or contour curves. Challenges involved in estimating the surface by curves are also identified.

Mots clefs

3D face recognition, facial surface, curve based representation, contour, profile.

1 Introduction

For long, face recognition has been a two-dimensional discipline. Although the 2D recognition systems do well in recognition task under some constrained conditions, they have encountered many challenges to cope with variations in lighting conditions, head poses, face expressions and occlusion [1]. At the same time, technological improvements are making 3D surface capturing devices affordable for security purposes. These newly-developed 3-D face scans encode the anatomical structure of the face, and hence are independent of ambient illumination conditions and pose variations [2]. As a result, face recognition shifts from 2D to 3D. This means that in the actual face recognition systems, the problem is no longer the comparison of 2D colour images, but the comparison of (textured) 3D surface shapes. Therefore, utilizing 3D shape information has capabilities for providing greater recognition accuracy. The 3D shape information has the obvious advantage that is an intrinsic property of the face and hence is invariant to illumination conditions.

Many approaches to 3D face recognition have been proposed during the past twenty years. Statistical Methods such as Principal Component Analysis (PCA) and Linear Discriminate Analysis (LDA) have been widely used for 2D facial images [3]. Applying them to 3D facial models instead of 2D images has been investigated by Chang et al [4]. More efforts are put to directly use the surface geometry that describes the face. Lee et al [5] use the mean and Gaussian curvatures to segment the facial images and create an Extended Gaussian Image (EGI) of each region to represent the face. Gordon [6] discusses face recognition based on depth and curvature features. In this work 3D facial features are extracted, such as nose bridge and eye corners and comparison between two faces is based on their relationship in feature space. A set of algorithms extracted vectors of geometric features, such as width and position. Lee et al [7] reported a technique where positions, distances, ratios of distances, and angles between eight fiducial points were employed as features with a support vector machine classifier. Another important direction of 3D face recognition methods is based on extracted curves (profiles and contours) to represent the face surface shape. This type of surface representation must answer the following issues:

- How to define these curves on the facial surface?
- How to extract these curves from 3D scans?
- How to quantify deformation between two surfaces by comparing shapes of corresponding curves?

In the present work, we give an overview of facial surface representations via curves within the scope of 3D face recognition. For each of the representations, we will shortly describe the mathematical formulation behind it. Related research using these representations will be discussed and a comparison between these methods will be given.

The rest of this paper is organized as follows: Section 2 gives an overview of curve based 3D facial surface representations. Section 3 states some of the most important challenges of these representations.

2 Overview of curve based 3D facial surface representations

Before investigating on curves, it is indispensable to take into account the point cloud representation of facial surface. It is without doubt the simplest one. In the 3D case, it consists of an unordered set of points *x*, *y*, and *z*-

coordinates that lie on the surface. Point clouds are most often the output created by 3D scanners and can be the base of most of the 3D surface based representations. This is why a large amount of algorithms were developed for this type. A very popular method for 3D surface alignment is the Iterative Closest Point (ICP) algorithm. In 3D face recognition, ICP is frequently used for surface registration [8,9,10,11]. Three-dimensional face shapes are often modelled with a point cloud based statistical model, generally with a PCA model as in [8,12,13]. However, Point clouds are incomplete surface description. This means that surface is known only at some sparse point locations. This is exactly the main drawback of this surface representation.

Curves are also sparse surface representations. They can even be sparser than point clouds, but can also be made to approximate the surface as good as wanted. The main idea is to represent shapes by the union of curves. The curve itself can be represented by a set of connected points or as a parametric form. In this paper, we are interested in works representing facial surface by curves witch can be Contours or profiles. Table 1 gives a summary of these researches, their important elements, advantages and limitations.

2.1 Facial surface representation by Contour curves

Contour curves are closed, non intersecting curves on the surface. Mostly, they have various lengths. According to the extraction strategy, different types of contour curves can be found. Isodepth curves are obtained by translating a plane through the 3D face in one direction and considering *n* different intersections of the plane and the face. *n* is the number of contours used to estimate the facial surface. The intersecting plane is positioned perpendicular to and translated along the gaze direction (*z*-axis). Hence, isodepth curves are level curves situated at equal *z*-values. Isoradius contours are space curves defined by the locus on a 3D surface that is a known fixed distance relative to some predefined reference point. Theses contours are obtained from an intersection of the face with concentric spheres with different radius $r = \sqrt{x^2 + y^2 + z^2}$ and generally centred on the nose tip point. An isogeodesic curve is a contour with each point of the curve on an equal geodesic distance (shortest path) to a reference point. A geodesic distance between two points is defined as the arc length of the shortest path between these two points along the surface and denoted by a Geodesic Distance Function (GDF), witch is a continuous function on the facial surface. Within the surface, iso-geodesic curve of level c is defined as curve satisfying the following condition [14]:

$$P^C = \{p / g(p) = c, p \in S\}$$

Where S is a face surface in R^3, and $g_S(.)$ is a GDF on S.

To extract geodesic curves, specific algorithms are used such as: fast marching [2,15], fast sweeping [16], Path straightening algorithm [17] and shooting method [19].

As mentioned before, Curves are non-complete surface representations, implying that the surface is only estimated by a fixed number of curves depending on the application; coarse or fine representation needed. On the one hand, this implies a loss of information, on the other hand lower storage requirements. In order to construct contour curves, a reference point is fixed. In 3D face recognition mostly the nose tip is detected and manually or automatically extracted.

Based on the hypothesis that expression-induced surface variations can approximately be modelled by isometric transformations which keep geodesic distances between every point pair on the surface almost invariant, isogeodesics represent low sensitivity to expression variation. Then they are most popular curves.

Feng et al. [14] divided the isogeodesics in small segments of equal arc length that form the basis of trained face signatures. So, they focused on local regions to make the signature independent of the starting point of a curve. They used the Fels-Olver construction and the 3D analog of Hann-Hickerman integral variables to derive integral invariants for curves in 3D subjected to the Euclidean group. The space curves in 3D are then mapped to the 2D invariant space, where there are no transformation effects, and matching space curves under transformation in 3D is reduced to matching signatures. The cosine distance is used to measure the similarity between signatures.

Jahanbin et al. [2] extracted from each isogeodesic five shape descriptors: convexity, ratio of principal axes, compactness, circular and elliptic variance. These features are trained with Linear Discriminant Analysis (LDA) and Support Vector Machines (SVM). With various experiments, they showed that LDA followed by Euclidean distance verifier outperforms linear SVM.

Miao et al. [15], compared two neighbouring isogeodesic distance curves, and formalized the evolution between them as a one-dimensional function, named evolution angle function, which is Euclidean invariant. As a result, the problem of comparing surfaces can be solved by comparing two sets of one-dimensional discrete function. To avoid the absence of the mouth regions from faces: first, a symmetric plane is detected, and each iso-curve is divided into two parts. Secondly, these two parts were independently parameterized by arc length, with the starting points at the top. Finally, they were combined to form parameterization of the whole curve.

Mpiperis et al. [16] proposed a 2D+3D face recognition algorithm where facial expression in both range and portrait representation of the face is compensated using the geodesic polar parameterization of facial surface as seen in Figure 1. Hence, they mapped the isogeodesic curves to concentric circles on a plane using a piecewise

Table 1*: Summary of curve based researches for 3D face recognition*

Reference	Used data	Needed Reference	Curve type	Number of curves	Data Base	Number of persons	Number of images	Size of images	Reported performance	Advantages	limitations
Samir[17]	Range	Nose tip	closed, planar	a: 5 curves b: 6 curves	a: FSU (300 images) b: Notre Dame (740 Scans)	a: 50 b: 162	a: 5faces /per gallery rest :test b: 470 gallery 270 test	a: 376 X 449 b:/	a: 92% b: 90.4	-Invariant to planar motion and global scale change	Gaze direction changes
Feng[14]	Mesh	Nose tip	closed, 3D	20 curves	FRGCv2 (spring 2003, 2004)	222 training 222 test	1 to 10 training 1 to 12 test	/	95%	- No Registration -Pose, expression invariant	Open mouth (excluded)
Miao[15]	Mesh	Nose tip	Open, planar	40 curves	FRGCv2 (spring 2004)	30 training 50 test	4/per training 50 neutral gallery 150 test	180x120	100% neutral faces 93.64% non neutral faces	-Euclidian transformations invariant	Open mouth (excluded)
Jahanbin [2]	Range	Nose tip	closed, planar	03 each type	1196 subject (see text)	10 training 10 client 109 impostor	383 training 389 client 424 impostor	751 x 501	2.58 EER% isogedesic 9.07 EER% isodepth	-expression invariant	Pose and size changes
Pears[18]	Mesh + intensity	Nose tip	closed	06	non-standard pose/expression data set (see text)	30	12 images /per	/	EER of 21.91%, (single signal , single contour)	-Invariant to pose variations -Good alignment -	Bad in mouth region under expression
Tang[20]	Mesh + texture	Nose tip	open	Vertical + horizontal	BJUT-3D	70	03 images /per	/	97.1%	No training phase	Pose changes
Haar[22]	/	Nose tip	Closed contours	45 profiles 08 contours	SHREC'08	/	427 scans	/	91.1%	Pose normalization	Large expression variations
Mpiperis [16]	Range	Nose tip + reference path	Closed Circles, open paths	/	a: Database1 b: Database2 (see text)	100	1500 (Single Neutral image/per as gallery Rest: prob)	a: 2500 avg vertices b: 576 X 766	-84.4 to 95% (depth) -4.9 to 15. 4 EER% (colour)	Handles open mouth under isometric transformations	Expression with strong intensity
Daoudi [23]	Mesh	Nose tip	Closed Circles, open paths	/	FSU	/	96 neutral: gallery 96 non neutral:probe	/	Verification:92% at 8% (neutral probe)	Invariant to rigid motion	-Nose type localisation -Expression variation

(When two databases are used, **a**: first base and **b**: second base**;** **/**: non mentioned in the paper **; /per**: for each person) linear warping transformation and create corresponding geodesic polar attribute images. Recognition is reduced to matching 2-D images which is a well-studied problem. These images contain deformation invariant attributes of the surface, such as colour and shape information.

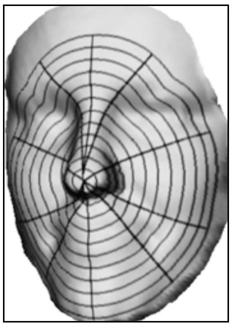

Figure 1 - *Geodesic paths and circles defined over a face surface (nose tip is geodesic pole) [16]*

To analyse the space of facial surfaces and to propose a framework of calculus on its manifold, Samir et al. [17], exploited the concept of geodesics at three distinct levels. The first use is in defining geodesic distances between any two points on a facial surface. This geodesic is the shortest of all paths between the two points contained completely in the surface. The second use of geodesics is in studying shapes of facial curves. This use involves construction of geodesic paths between any two facial curves on the space of 3D closed curves. Using Riemannian geometry, facial surfaces shape analysis is done by finally finding geodesic path between any two facial surfaces on the space of facial surfaces. As statistical tool, they have used these geodesics to define and compute the Karcher (intrinsic) mean of several facial surfaces in this Riemannian manifold.

Sphere based isoradius curves are used by Pears et al. in [18]. They encoded the whole facial surface using a dense set of contours around a single point of interest; nose tip, and extracted 3D shape properties along isoradius contours, such as facial curvature (change in facial surface normal) and the curvature of the isoradius contour itself. Due to the infinite rotational symmetry of a sphere, the representation is invariant to pose variations. Using this representation, registration can be implemented using a simple process of 1D correlation resulting in a fast and non iterative algorithm having a comparable accuracy to ICP and being robust to the presence of outliers.

Samir et al. [19] represented facial surfaces using a union of level-set curves of the depth function with respect to the nose tip named isodepth curves and constructed a shape space of curves of interest. Consequently, 3-D facial surfaces are implicitly compared by finding geodesic paths on this space and measuring lengths of these paths witch provide an intrinsic metric for comparing shapes of corresponding curves.

Jahanbin et al [2] used isodepth curves in the same way as they did with isogeodesics.

2.2 Facial surface representation by profile curves

Profile curves on the contrary are open and result from intersecting a facial surface with a plan having a predefined orientation; they have a starting and an end point. For 3D faces, the starting point is most frequently a point in the middle of the face, mostly the nose tip, while the end point is often at the edge of the face. There exist an infinite number of profile curves in between those points.

Profile curves are used by Tang et al. in [20]. They extracted vertical and horizontal profiles which contain the nose tip. To integrate both shape and texture information to represent 3D faces, vertices on the two profiles are extracted, ordered by their adjoining relationship and stored by their coordinates and texture. A normalization step (translation, rotation, scaling) is then done on each profile. By fusing texture and shape of vertical and horizontal profiles, they reached high recognition score.

Using five manually identified landmark points within a sub-surface composing of eyes and whole nose, Han et al. [21] determined two profiles. One is the horizontal curve passing by the two eyes. The other is the vertical symmetry curve as seen in Figure 2. Gaussian Curvature values are computed along these profile curves and used as features. By analysing the curvature plots, they denoted that eye balls shape and its curvature degree are unique for each individual.

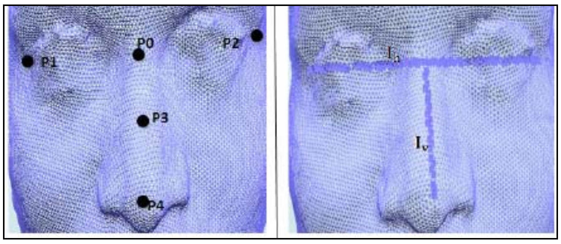

Figure 2 - *Sub-surface with landmarks illustration, vertical and horizontal profiles [21]*

Profile and contour curves are also associated to get more accurate representation. This association is adopted by Haar et al. in [22]. With the reference point taken on the nose tip, they extracted contour curves with same z value and profiles over the face surface in different directions. The information of each 3D face is reduced to a small set of 720 3D sample points. Hence, Comparison between faces is done using the weighted distance between corresponding sample points on the curves.

An other combination is done by Daoudi et al. [23] to impose a coordinate system on facial surfaces. It is the curvilinear coordinate system, in which one coordinate measures the distance of a point from the tip of the nose and its level curves are facial curves. The other coordinate measures distances along these curves; level curves of this coordinate are orthogonal to the facial curves. For comparing facial shapes under this representation, they constructed geodesic paths between curvilinear coordinate system curves by using elastic metric which allows to realize optimal deformations between surfaces.

3 Challenges for curve based 3D facial surface representations

One limitation of the curve based representations of facial surfaces is that they are susceptible to changes in gaze direction. To mitigate the effect of pose variation in recognition performance, an accurate gaze alignment step is required that proves to be very costly and difficult.

The second serious limitation involves sensitivity to change of facial expression between the enroled image and the image to be recognized. A robust facial recognition system should be able to handle variation in expression. Approaches that effectively assume that the face is a rigid object will not be able to handle expression change. In fact, changes in facial expressions integrate local motion and change the shapes of facial parts to some extent. One solution to handle this problem is to adopt partial human biometrics based on local shape analysis. This is done by looking for facial parts which are less affected by expression changes. Drira et al. [24] projected past work in Riemannian analysis of shapes of closed curves on nasal surfaces. This choice is due to the stability of nose data collection and the invariance of nasal shape under expressions. On a gallery set of neutral faces of 209 subjects from FRGCv2 dataset, they recorded a 76.1% rate using only seven curves in an identification scenario.

Another application is presented by Maalej et al. [25]. In the context of facial expression recognition, they extracted several relevant regions of a given facial surfaces. They locally projected isogeodesic path idea by representing each patch with a set of closed curves, as illustrated in Figure 3.

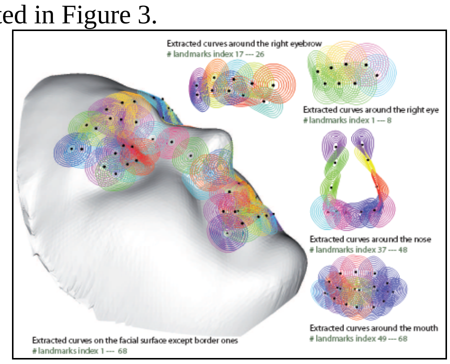

Figure 3 - *Curves extraction for facial patches centred on multiple reference points [25]*

Even 3D face recognition are expanding with important potential applications in this direction, there are many challenging research problems still to be addressed. Moreover, expanded use of common datasets and baseline algorithms in the research community will facilitate the evaluation of the state of the art in this area.

References

[1] L. Wenlong, Z. Yin, J. Wu, Y. Xiong. 3D Face Recognition Based on Local/Global Shape Description. In IEEE International Conference on Information Technology and Computer Science, 2009.

[2] S. Jahanbin, H. Choi, Y. Liu, and A. C. Bovik. Three dimensional face recognition using iso-geodesic and iso-depth curves. In BTAS ’08: Proceedings of the IEEE Second International Conference on Biometrics Theory, Applications and Systems, Arlington, Virginia, USA, 2008.

[3] L. Chen, H. Liao, M. Ko, J. Lin and G. Yu. A new LDA-based face recognition system which can solve the small sample size problem. In IEEE Pattern Recognition 33 (10), 2000.

[4] K. Chang, K. Bowyer and P. Flynn. Face recognition using 2D and 3D facial data. In Multimodal User Authentication Workshop, 25–32, 2003.

[5] J. Lee and E. Milios. Matching range images of human faces. In International Conference on Computer Vision (ICCV), 722–726, 1990.

[6] G. Gordon. Face recognition based on depth maps and surface curvature. In SPIE, 234–274, 1991.

[7] Y. Lee, H. Song, U. Yang, H. Shin, and K. Sohn. Local feature based 3D face recognition. In Audio- and Video-based Biometric Person Authentication, International Conference on, LNCS, (3546), 909–918, 2005.

[8] X. Lu and A.K. Jain. Deformation analysis for 3D face matching. in WACVMOTION ’05: Proceedings of the Seventh IEEE Workshops on Application of Computer Vision, (1) 99–104, Washington, DC, USA, 2005.

[9] Y. Wang, G. Pan, Z. Wu and Y. Wang. Exploring facial expression effects in 3D face recognition using partial IC. in P. Narayanan (ed.), Computer Vision ˝U ACCV 2006, (3851) 581-590 of Lecture Notes in Computer Science, Springer Berlin/ Heidelberg, 2006.

[10] N. Alyüz, B. Gökberk and L. Akarun. A 3D face recognition system for expression and occlusion invariance. In BTAS ’08: Proceedings of the IEEE Second International Conference on Biometrics

Theory, Applications and Systems, Arlington, Virginia, USA, 2008.

[11] I. A. Kakadiaris, G. Passalis, G. Toderici, M. N. Murtuza, Y. Lu, N. Karampatziakis and T. Theoharis. Three-dimensional face recognition in the presence of facial expressions: An annotated deformable model approach. IEEE Transactions on Pattern Analysis and Machine Intelligence 29(4): 640–649, 2007.

[12] B. Amberg, R. Knothe and T.Vetter. Expression invariant 3D face recognition with a morphable model. In FG ’08: Proceedings of the 8th IEEE International Conference on Automatic Face and Gesture Recognition, IEEE Computer Society, Amsterdam, The Netherlands, 2008.

[13] F. Al-Osaimi , M. Bennamoun and A. Mian. An expression deformation approach to non-rigid 3D face recognition. In International Journal of Computer Vision 81(3): 302–316, 2009.

[14] S. Feng, H. Krim, and I.A Kogan. 3D face recognition using euclidean integral invariants signature. In SSP ’07: IEEE/SP 14th Workshop on Statistical Signal Processing, , 156–160, Madison, WI, USA , 2007.

[15] S. Miao and H. Krim. 3D Face Recognition Based On Evolution Of Iso-Geodesic Distance Curves. In IEEE, ICASSP, 1134-1137, 2010.

[16] I. Mpiperis, S. Malassiotis, and M. G. Strintzis, “3-d face recognition with the geodesic polar representation. In information Forensics and Security, IEEE Transactions (2) no. 3, 537-547, Sept. 2007.

[17] C. Samir, M. Daoudi and A. Srivastava. A Framework of Calculus on Facial Surfaces. In 14th International Conference of Image Analysis and Processing - Workshops , ICIAPW , 2007.

[18] N. Pears and T. Heseltine. Isoradius contours: New representations and techniques for 3D face registration and matching. In 3DPVT’06: Proceedings of the Third International Symposium on 3D Data Processing, Visualization, and Transmission, IEEE Computer Society, 176–183, Washington, DC, USA, 2006.

[19] C. Samir, A. Srivastava, and M. Daoudi. Three-Dimensional Face Recognition Using Shapes of Facial Curves. In IEEE Transactions On Pattern Analysis And Machine Intelligence, 1858-1863, 2006.

[20] H. Tang, S. Yanfeng, B. Yin and G. Yun. 3D Face Recognition Based on Facial Profiles. In IEEE, 2009.

[21] X. Han, H. Ugail and I. Palmer. Method of Characterising 3D Faces Using Gaussian Curvature. In IEEE, 2009.

[22] T. Haar, F. B. and R.C. Veltkamp. SHREC’08 entry: 3D face recognition using facial contour curves. In SMI ’08: Proceedings of the IEEE International Conference on Shape Modeling and Applications, 259–260, Stony Brook, NY, USA, 2008.

[23] M. Daoudi, L. Ballihi, C. Samir, A. Srivastava. Tree-Dimensional Face Recognition Using Elastic Deformation Of Facial Surfaces. In IEEE, ICME, 2008.

[24] H. drira, B. Ben Amor, A. Srivastava, M. Daoudi. A Riemannian Analysis of 3D Nose Shapes For Partial Human Biometrics. In 12th International Conference on Computer Vision (ICCV), IEEE, 2009.

[25] A. Maalej, B. Ben Amor, M. Daoudi, A. Srivastava, S. Berretti. Local 3D Shape Analysis for Facial Expression Recognition. In IEEE, International Conference on Pattern Recognition, 2010.