3D Human Face Segmentation using Curvature Estimation

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ABSTRACT

This paper presents the representation and its shape analysis of face by features based on surface curvature estimation and proposed rotation vector of the human face. Curvature-based surface features are well suited to use for experimenting the 3D human face segmentation. Human surfaces are exactly extracted and computed with parameters and rotated by using active surface mesh model. The estimated features were tested and segmented by reconstructing surfaces from the face surface and analytically computing Gaussian (K) and mean (H) curvatures without threshold.

Curvature Estimation을 이용한 3차원 사람얼굴 세그멘테이션

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요 약

본 논문에서는 3차원 사람얼굴의 굴곡표면에 대하여 특징 값들을 추출하여 회전벡터를 이용하여 회전한 후 그들을 분석, 표현하는 방법을 제안한다. 또한 실험을 통하여 정확하게 추출된 굴곡표면의 특징 값들은 3차원 사람얼굴을 세그멘테이션 하는데 적용되었다. 사람얼굴의 표면은 메쉬(mesh) 모델을 사용하여 파라메타를 계산, 추출하였으며, 추출된 특징 값들은 얼굴표면을 Gaussian과 Mean 곡면 분류표(classification)를 사용하여 임계 값을 사용하지 않고 3D 얼굴표면을 세그멘테이션 하였다.

Key words: curvature estimation, range data, face segmentation, wavefront

1. Introduction

The face recognition problem has received a great deal of attention in the computer vision community. In some senses it is one of the most difficult of all the visual recognition tasks because it requires differentiating among objects, which vary only subtly, from each other. Yet humans perform the task effortlessly many times a day and have the capacity for storing and distinguishing among thousand of faces. Most segmentation schemes rely on surface curvatures to obtain an intimate description of the surface. While a single curvature estimate of a two dimensional contour provides a straightforward and complete description of its local properties, the addition of an extra dimension shows an amazing jump in the degree of complexity. For starters, a single number is insufficient to describe the local properties of the surface completely. In fact, six such numbers are required and form the parameters for the two fundamental forms described later. However, the six numbers are unwieldy to work with and a more compact representation is desirable. Several such representation have been proposed, the most popular being the Mean and Gaussian curvatures.

접수일 : 2003년 2월 21일, 완료일 : 2003년 4월 8일
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The segmentation scheme relies on these parameters to obtain a classification. Curvature-based surface features are well suited for use in human face segmentation.

Range sensors now produce data of such resolution and accuracy that, with careful treatment of noise, accurate curvature calculations can be made for the human face. The availability of curvature data opens up many new avenues for face recognition methods. unsuitable form will be returned for retyping, or canceled if the volume cannot otherwise be finished on time.

Range image segmentation techniques can primarily be classified into two distinct categories edge based (or surface-discontinuity based) and region based (or surface based)[1]. A similar segmentation technique was described by Han et al.[2] in which planar regions are first extracted by histogram analysis of normal values, the cylindrical regions are extracted next by the computation of axis information and projection to extract the resulting circles, and finally spherical regions are extracted by estimating possible center points for each pair of surface points and voting to decide the majority value of the center. Seti and Jayamurthy[3] handled spheres and ellipsoids in addition to planes, cylinders and cones by classifying surfaces using characteristics contours. Besl and Jain[1] used the sign of the Gaussian and mean curvatures computed at each point (HK sign map) to classify each point as one of eight qualitative surface types. Haralick et al.[4,11] classifies each point as one of six qualitative surface types: peak, pit, ridge, ravine, saddle, flat and hillside.

Flynn and Jain[5] describes a surface classification scheme based on the quadratic surface model. A sample of surface points is classified as planar or non-planar through two hypothesis tests. Ioannis Doros and Bernard[6] presented a method for detecting significance geometric features on the 3D body surface. These features (such as ridges and umbilic points) do not require a prior anatomical information and hardware-independent. Richard[7] presented a method of explicitly parameterizing surfaces from volumetric data to use medical images. This method produces low errors in surface position with adequate surface extraction. Fig. 1 briefly presents the whole process which derives a human face segmentation from range image.

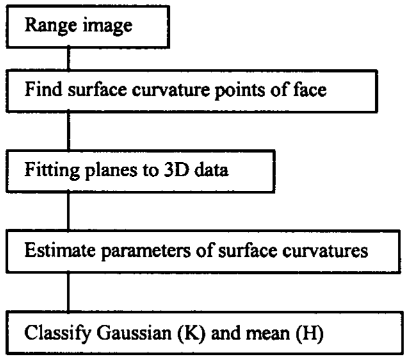

Fig. 1 Flowchart of segmentation algorithm

2. Surface curvatures

Our first step in building a description of the surface for a human face recognition system is to evaluate properties of the surface that can be used in its segmentation and classification that is in turn, the precursor to obtain a symbolic description of the human face. While a single curvature estimate of a two dimensional contour provides a straightforward and complete description of its local properties, the addition of an extra dimension shows an amazing jump in the degree of complexity. In fact, six such numbers at least are required and form the parameters for the two fundamental forms described below. However, the six numbers are unwieldy to work with and a more compact representation is desirable.

The tradition method for fitting planes to a set of 3D points is linear least squares. Unfortunately, the fitting method implicitly assumes that two of the three coordinates are measured without error, and that these two coordinates adequately support plane being fitted. In this situation (multiple range images), these two assumptions are not valid. Through registration of multiple range images of the same surface, the ensemble of surface points could have error in all three coordinates. Additionally, in the object-centered coordinate system, the surface can be in any orientation. To overcome these problems we resort to a classical multivariate method which explicitly allows us to extract linear dependencies (such as planes) in a data set.

2.1 Surface fitting planes to 3D

The method of principal components[8] yields a planar fit which optimal in a least squares sense, with quality of the fit being independent of the embedding of the surface in 3D space. The principal components of a set of 3D points may be obtained by extracting the eigenvalues and corresponding eigenvectors of its sample covariance matrix [8]. Let eigenvalues be denoted as λ_1, λ_2, and λ_3 with $\lambda_1 > \lambda_2 > \lambda_3$, and their associated eigenvectors be v_1, v_2, and v_3. The eigenvectors define a new basis for 3D using the data. The eigenvector v_1 corresponding to the largest eigenvalue λ_1 is the direction along which the data has the largest variation, and the value of the variance in that direction is λ_1. The eigenvector v_2, corresponding to the second largest eigenvalue λ_2 is the direction orthogonal to v_1 that has the largest variance in the data, and the value of that variance is λ_2. The v_3 is the vector product of v_1 and v_2 and and the variance along that direction is λ_3. If the original data is (u_x, u_y, u_z), then we use the formula for an arbitrary rotation about an arbitrary 3D axis to obtain a matrix Rv, which has property that

$$v_1 * Rv = [0 \quad 0 \quad 1] \tag{1}$$

In other words, the Rv matrix rotates v_1 into the Z axis. An angle θ about an arbitrary direction is given by the direction vector $U=(u_x, u_y, u_z)$. Here is the proposed rotation vector:

Rv =

$$\begin{bmatrix} u_x^2+\cos\theta(1-u_x^2) & u_x u_y(1-\cos\theta)-u_z\sin\theta & u_z u_x(1-\cos\theta)+u_y\sin\theta \\ u_x u_y(1-\cos\theta)+u_z\sin\theta & u_y^2+\cos\theta(1-u_y^2) & u_y u_z(1-\cos\theta)-u_x\sin\theta \\ u_z u_x(1-\cos\theta)-u_y\sin\theta & u_y u_z(1-\cos\theta)-u_x\sin\theta & u_z^2+\cos\theta(1-u_z^2) \end{bmatrix} \tag{2}$$

This plane fit minimizes the sum of squared perpendicular distance between the data points and the plane, and independent of the coordinate frame. In this respect, this method of fitting planes is better than methods of fitting such as least squares which require the specification of an appropriate coordinate system.

2.2 Least Squares Surface Fit

Once the local coordinate system obtained from principal components analysis[8,9] and tessellation has been fixed, a quadratic surface of the form

$$w=f(u,v)=a_1u^2+a_2uv+a_3v^2+a_4u+a_5v+a_6 \tag{3}$$

is used to find a least squares fit to the transformed data points. The transformation of the data points on the surface patch is from their original coordinate system to the local coordinate system derived from principal components analysis. The coordinates in the transformed space are given by

$$\begin{bmatrix} u_1^2 & u_1v_1 & v_1^2 & u_1 & v_1 & 1 \\ u_2^2 & u_2v_2 & v_2^2 & u_2 & v_2 & 1 \\ u_3^2 & u_3v_3 & v_3^2 & u_3 & v_3 & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ u_N^2 & u_Nv_N & v_N^2 & u_N & v_N & 1 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \\ a_6 \end{bmatrix} = \begin{bmatrix} w_1 \\ w_2 \\ w_3 \\ \vdots \\ w_N \end{bmatrix} \tag{4}$$

where x_0 is the vector of coordinates of the point at which the curvatures are being computed and x_i are the points in the neighborhood of x_0. The system of equations used to compute the quadratic least squares fit given by

$$u_i = [u_i \; v_i \; w_i]^T = V^T(x_i - x_0) \tag{5}$$

or

$$\mathbf{Aa} = \mathbf{w} \tag{6}$$

The best solution of **a** is one that minimize the squared error term

$$\varepsilon^2 = | w - Aa |^2 \tag{7}$$

and is given by

$$a = \left(A^T A\right)^{-1} A^T w \tag{8}$$

Having found the coefficients of the quadratic in above equation we can now compute the partial derivatives as

$$f_u = \frac{\partial f}{\partial u} = 2a_1 u + a_2 v + a_4$$

$$f_v = \frac{\partial f}{\partial v} = a_2 v + 2a_3 v + a_5$$

$$f_{uu} = \frac{\partial^2 f}{\partial u^2} = 2a_1$$

$$f_{uv} = \frac{\partial^2 f}{\partial u \partial v} = a_2$$

$$f_{vv} = \frac{\partial^2 f}{\partial v^2} = 2a_3 \tag{9}$$

3. Curvature estimation

A method of surface curvature estimation was presented by Flynn and Jain[5,9]. They classify the available techniques into two broad categories - analytic estimates and numerical estimates. Analytic methods estimate the curvature of a point on the surface based on a local surface fit called on a Monge patch. A Monge patch is a surface of the form

$$\mathbf{x(u,\ v)} = \mathbf{(u,\ v,\ f(u,\ v))} \tag{10}$$

The coefficient of the first fundamental form from[9] for such a face are given by

$$E = 1 + f_u^2$$

$$F = f_u f_v$$

$$G = 1 + f_v^2 \tag{11}$$

and the second fundamental form is

$$L = \frac{f_{uu}}{\sqrt{1 + f_u^2 + f_v^2}}$$

$$M = \frac{f_{uv}}{\sqrt{1 + f_u^2 + f_v^2}}$$

$$N = \frac{f_{vv}}{\sqrt{1 + f_u^2 + f_v^2}} \tag{12}$$

The Gaussian and mean curvature are given by

$$K = \frac{f_{uu} f_{vv} - f_{uv}^2}{\left(1 + f_u^2 + f_v^2\right)^2}$$

$$H = \frac{(1 + f_v^2) f_{uu} - 2 f_u f_v f_{uv} + (1 + f_u^2) + f_{vv}}{2\left(1 + f_u^2 + f_v^2\right)^{3/2}} \tag{13}$$

4. Face segmentation

Our objective is to obtain a representation of the object, that describes the object at a level of detail that is just sufficient to distinguish the object uniquely. The segmentation in patches of a depth image provides a small description of the reconstructed data by Mean (H) and Gaussian (K) classification table, Table 4.1.

Table 4.1 Surface description from Gaussian and mean curvatures

	H < 0	H = 0	H > 0
K < 0	Saddle ridge	Minimal surface	Saddle valley
K = 0	Ridge	Plane	Valley
K > 0	Peak	-	Pit

Besl and Jain[1] proposed the signs of the Gaussian (K) and Mean (H) curvatures computed at each point (HK sign map) to classify each points as one of eight different surface types described in Table 4.1. In Table 4.2, it is described eight different colors given by HK sign map. This lower level segmented description is then passed through a higher level surface approximation stage that uses an iterative region growing method based on variable order surface fitting. Flynn and Jain[10] described a surface classification scheme based on the quadratic surface model.

Table 4.2 Surface color map from Gaussian and Mean curvatures

	H < 0	H = 0	H > 0
K < 0	Yellow	Black	Blue
K = 0	Magenta	Green	Red
K > 0	Cyan	-	White

5. Experiments

The acquisition of range images of human face is not trivial. Very good image is provided by the range scanner of Cyberware. The system is based on a laser range finder and a rotation platform. Generally, the scanner yields data of very high accuracy and provides a panoramic, 360° view of the object. The image format in our experiment is 3D wavefront .obj file format which are text based files supporting both polygonal and free-form geometry (curves and surfaces). The image has 29,527 pixels with 58,211 triangles. For segmentation did take a little long time, we reduced number of pixels and triangles to segment it and rotated the image to use the rotation vector, formula (11). Since it would be crucial to study how stable this segmentation is from a person to another; for example, we wonder if the kind of quadric which approximates a given region of the face is rather invariant between different people.

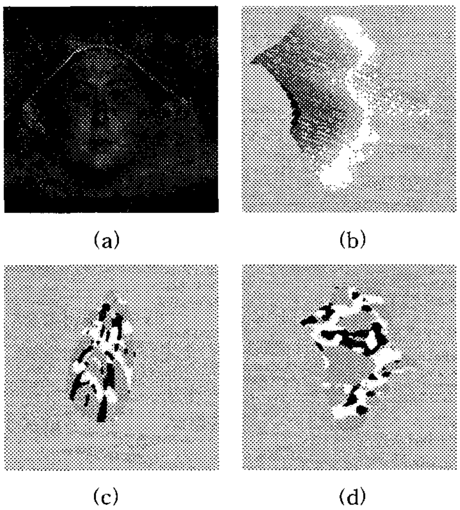

Fig. 2 Range face (a) and its 3D mesh component (b), rendered segmentation (c), and normal segmentation (d)

The bottom pictures of Fig. 2 successively shows the segmentation into 4 different classified description as given by Table 4.2. We can see that one region covers the forehead and nose and cheek peaks, one covers eyebrow and eye corner and nose valleys, one covers below of mouth and nose ridges and one covers eye pits.

6. Conclusion

In this paper, we have presented a segmentation of the human face into 3D color patches without threshold from range image of wavefront format. Even under the relatively analytic face model, the human face fitting problem is a difficult one to evaluate surface curvatures. We have shown that human face classification through Gaussian and Mean curvatures using surface curvature estimation and proposed rotation vector is to be a valid and good approach method for segmentation. In the future, we plan to develop other one, more realistic and complicate models with surface fitting processes and also evaluate a method of scalar features from 3D.

7. Acknowledgements

The authors would like to thank editorial members for helpful comments on our works. Thanks also to the Dr Boywer and Dr Flynn of Computer Vision Lab of University of Notre Dame, for providing range data.

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