POSTER: Geodesic Stripes Based Hierarchical Evaluation for 3D Facial Similarity

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ABSTRACT

Similarity evaluation of 3D face is the core issue in 3D face recognition. The article puts forwards a geodesic stripes based evaluation method which realizes assessment from global face to local parts. It can be used to make effective and comprehensive evaluation in many fields such as 3D face reconstruction, forensic science, archaeology etc. First, simplify each 3D face with a series of geodesic stripes and calculate distribution vector between each pair of stripes, which reflects 3D space distribution feature. Then through feature extraction on entire face, we get a distribution matrix which consists of all distribution vectors. The similarity between two distribution matrices directly shows the global similarity between two faces. We also extract geodesic stripes feature on local organs like mouth eye and nose to make a more accurate evaluation. The experimental results on SHREC2008 3D face database further testify that the hierarchical evaluation method is available and consistent with the subjective evaluation.

Keywords

Posture standardization, ICP (Iterative Closest Point), Geodesic stripes, Similarity calculation

1. INTRODUCTION

In the information age, there have been many researches on identity authentication with biological characteristics like face, fingerprints, iris, etc. The common 3D facial similarity evaluation is achieved by artificial and subjective means. This method is mainly to gather a certain amount of volunteers, and design different strategies to evaluate similarity by subjective visual [Ste06a]. Although the method is consistent with the human cognitive principles, it's time-consuming and labor-intensive [Qua07a]. In this article, a method is proposed from the geometric and numerical perspective to evaluate the similarity.

Similarity evaluation methods of general 3D model can be divided into geometric feature-based similarity evaluation and topological feature-based similarity evaluation. In addition, from early 90 's of last century，similarity evaluation is widely used in some professional 3D models like Biological molecules [Can03a][Rog03a], terrain stripe and mechanical elements [Kri03a]. Generally, besides using geometric feature and topological feature mentioned above, similarity evaluation of professional 3D models also use specific domain knowledge.

Similarity evaluation of 3D face is the core issue in 3D face recognition. At present, feature point based method is widely used in morphometry [Ric02a]. Feature points based method needs to precisely extract feature points like tip of the nose, mouth corner and other parts, then construct feature vector to measure the similarity between different faces [Tho05a]. However, it's hardly to extract feature point in smooth face area like cheek and forehead. Therefore this is a great challenging problem. Gupta proposes an efficient method of extracting feature points to overcome the difficulty [Gup07a], which uses these feature points defined by Farkas [Far87a]. Face curve based method uses meaningful contour curve to present the face model [Mip07a][Sam06a][Ter08a]. The contour curve actually consists of discrete points which have equal distance to nose tip. Then the curve characteristics are compared to calculate face similarity [Ter08b][Fen07a]. Here we apply a contour stripe based method to make an evaluation from global face to local organs.

2. FEATURE EXTRACTION

A stripe is a set of vertexes which share the same distance to the nose tip. Hence, the relationship between two stripes can be described by the space distribution feature between two sets of vertexes through statistical analysis, In the article, to calculate space distribution feature, we refer the 3DWW (3D Weighted walkthroughs) [Ber03a] between two entities in space. Meanwhile, Berretti also applied iso-Geodesic stripes to extract feature of 3D face. Compared with Berretti's 2010, we make two major improvements on the way of feature extraction and the way of similarity calculation. The following passage will illustrate the space distribution feature between two stripes.

Definition of space distribution feature

Each stripe consists of a group of discrete vertexes, and the group of vertexes can approximately represent a part of surface. Here one improvement is use the discrete statistic to replace the numerical differentiation on face surface [Ber10b]. In this case, the computation efficiency is greatly increased, while the computation result is almost same. According to the different position in 3D space, each pair of points has different space distribution feature ω(i,j,k). as in (1-2)

$$\omega(\mathrm{i},\mathrm{j},\mathrm{k}) = \omega(F(a_x - b_x), F(a_y - b_y), F(a_z - b_z)) \quad (1)$$

$$F(\mathrm{x}) = \begin{cases} 1 & \mathrm{x} > б \\ 0 & |\mathrm{x}| <= б \\ -1 & \mathrm{x} < -б \end{cases} \quad (2)$$

Here δ is a threshold, and the distribution feature ω(i,j,k) has 27 kinds in total. There are two sets of vertices. Any vertex in set A and any vertex in set B can make up a pair of vertices ,which corresponds to a distribution feature , According to the combination principle ,the number of distribution feature between two sets of vertices is . Then calculate distribution feature, as in (3-14).

$$\omega \mathrm{H} = \omega_{1,1,1} + \omega_{1,-1,1} + \omega_{1,1,-1} + \omega_{1,-1,-1} \quad (3)$$

$$\omega \mathrm{V} = \omega_{-1,1,1} + \omega_{1,1,1} + \omega_{-1,1,-1} + \omega_{1,1,-1} \quad (4)$$

$$\omega \mathrm{D} = \omega_{1,1,1} + \omega_{1,-1,1} + \omega_{-1,1,1} + \omega_{-1,-1,1} \quad (5)$$

$$\omega \mathrm{XY} = \omega_{-1,-1,1} + \omega_{1,1,1} + \omega_{1,1,-1} + \omega_{-1,-1,-1} \quad (6)$$

$$\omega \mathrm{XZ} = \omega_{-1,-1,-1} + \omega_{1,-1,1} + \omega_{1,1,1} + \omega_{-1,1,-1} \quad (7)$$

$$\omega \mathrm{YZ} = \omega_{-1,1,1} + \omega_{1,1,1} + \omega_{1,-1,-1} + \omega_{-1,-1,-1} \quad (8)$$

$$\omega \mathrm{H}_0 = \omega_{0,1,1} + \omega_{0,-1,1} + \omega_{0,1,-1} + \omega_{0,-1,-1} \quad (9)$$

$$\omega \mathrm{V}_0 = \omega_{-1,0,1} + \omega_{1,0,1} + \omega_{-1,0,-1} + \omega_{1,0,-1} \quad (10)$$

$$\omega \mathrm{D}_0 = \omega_{1,1,0} + \omega_{1,-1,0} + \omega_{-1,1,0} + \omega_{-1,-1,0} \quad (11)$$

$$\omega \mathrm{HV}_0 = \omega_{0,0,1} + \omega_{0,0,-1} \quad (12)$$

$$\omega \mathrm{HD}_0 = \omega_{0,1,0} + \omega_{0,-1,0} \quad (13)$$

$$\omega \mathrm{VD}_0 = \omega_{1,0,0} + \omega_{-1,0,0} \quad (14)$$

The value of ω(i,j,k) is the distribution probability in all m*n distribution features. The specific calculation method refers to the following equation.

$$\omega_{i,j,k}(A,B) = \frac{num(\{(a,b)\})}{m*n} \quad (15)$$

$$F(a_x - b_x) = i \,\&\, F(a_y - b_y) = j \,\&\, F(a_z - b_z) = k \quad (16)$$

The num ({(a, b)}) is the number of the pair of vertexes (a, b) in the set.At last, the space distribution feature between two sets of A and B W(A,B)can be described by a vector（ω H,ω V,ω D,⋯ω HV0,ω HD0,ω VD0）T ,whose dimension is 12.

Geodesic stripes extraction

With the evolvement and optimization of the geodesic distance algorithm, there are many applications in the research area of mesh segmentation and mesh smoothing [Pey04a]. The research has testified that geodesic stripes perform well when used in 3D face recognition [Sam06a]. In order to calculate the geodesic distance from nose tip to every vertex on the 3D model, we apply the fast exact geodesic method which is demonstrated in paper [Vit05a].Figure 1 is the face which is represented with the geodesic stripes.

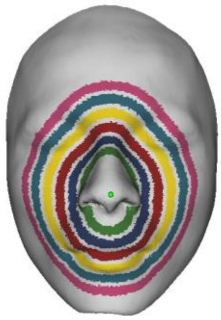

Figure 1.Face simplified with geodesic stripes

3. SIMILARITY CALCULATION

Based on the feature extraction in the above passage, the similarity between two faces can be converted into the similarity between distribution vectors. As for the distribution vectors, the article [Ber10b] calculates distribution vectors separately and make weighted sum of them. However, from a different perspective, we treat the 3D face as a whole entity and arrange all the distribution vectors into a distribution matrix, whose size is K *（K-1）/2 columns and 12 rows. Therefore, the similarity between two distribution matrices can directly reflect the similarity between two faces. In the next, the feature of two face models can be expressed by matrix M1 and M0, the similarity is calculated, as in (17) and (18).

$$S(M_1, M_0) = R(M_1 - M_{\min}, M_0 - M_{\min}) \quad (17)$$

$$M_{\min}(i,j) = \min\{M_0(i,j), M_1(i,j), \ldots M_K(i,j)\} \quad (18)$$

$R(M_1, M_0)$ is 2D correlation coefficient which is often used to measure deformation (engineering), displacement, and it is also widely applied in many areas of science and engineering [Sut09a]. The value of correlation coefficients fall in the range between 0 and 1, where 1 indicates perfect similarity between two matrices, and 0 indicates no similarity. Any value in between is a measure of the extent of similarity [Guf06a].

4. FEATURE EXTRACTION ON LOCAL ORGANS

In fact, it's necessary and meaningful to evaluate facial similarity on local organs (mouth, eye, nose). To make a more accurate and comprehensive assessment. Here we can segment local organs according to the geodesic distances from a reference point. As shown in Figure2, local organs represented with geodesic stripes.

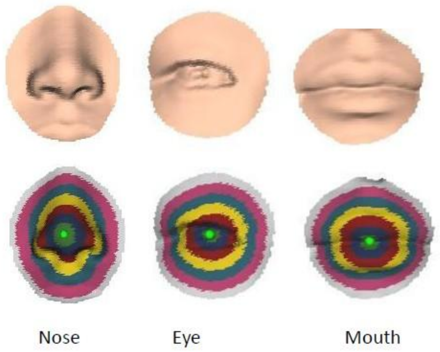

Figure 2.Local organs with geodesic stripes

5. EXPERIMENTAL RESULTS

Experiments on SHREC2008 database

In order to check the effect of the method based on geodesic stripes, we test the algorithm with the database SHREC 2008 (3D Shape Retrieval Contest 2008). The experimental results are shown in Figure 3.

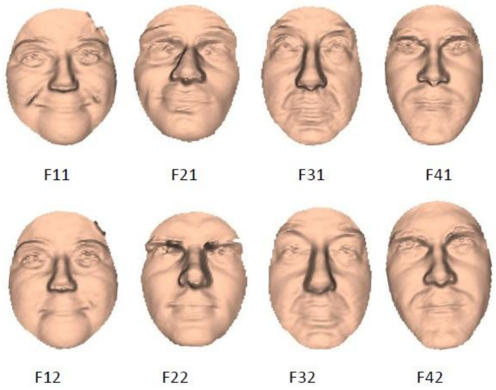

Figure 3.Face recognition results of 4 individuals

The first row (F1, F2, F3, F4) represents the inputs, and the second row represents the recognition results. Meanwhile, the table 1 is the similarity results between different individuals. It is not difficult to find that the similarity result of the same individual is big, and the similarity result among different individuals is relatively small.

Global Face	Similarity Results			
	F12	***F22***	***F32***	***F42***
F11	**0.9736**	0.7386	0.7126	0.8548
F21	0.7420	**0.9386**	0.9098	0.8285
F31	0.8359	0.8797	**0.9907**	0.8688
F41	0.8933	0.8640	0.9003	**0.9809**

Table 1.Recognition results on SHREC2008

Experiments on evaluation of 3D facial reconstruction

In experiment we apply the previous the method to evaluate the similarity both on global face and local organs to further prove the effect of the hierarchical evaluation. Table2 is the similarity result to compare the quality of two reconstruction methods. They are the quantitative similarity results for global face, nose, eye and mouth. The experimental results show that F3 is more similar to F1 than F2 toF1, which also means the regional method perform better. The experimental results show that the similarity of organs contributes to the global similarity.

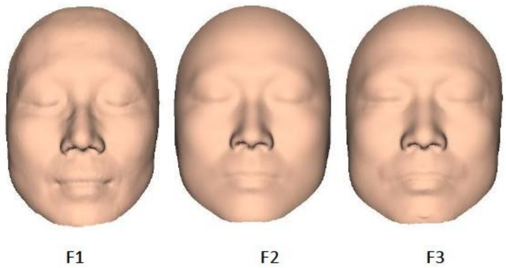

Figure 4.Reconstructed results for origianl face F1, F2 is reconstructed faces with global method and F3 is with the regional method

Face	Similarity Results			
	Global	***eye***	***nose***	***mouth***
F1:F2	0.8911	0.8542	0.8734	0.8132
F1:F3	0.9263	0.8701	0.8921	0.8347

Table 2.Evaluation of face reconstruction method

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