Reconstruction of 3D Face Model from Single Shading Image Based on Anatomical Database

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Abstract

We propose a method to reconstruct 3D face model from a single face-frontal shading image based on a database of the original 3D face shapes which are created according to anatomical basis of the human head. In the proposed method, we reconstruct the 3D shape of the face from the input shading image by estimating small number of eigenvalues taken by Principal Component Analysis(PCA) of the anatomical database of the head, rather than directly recovering the shape from the input shading image. The eigenvalues are estimated based on the optimization of the error value computed by comparing shading information of input image to that of model image created from the shape represented by the eigenvalues. For evaluating the effectiveness, we reconstruct various face shapes from single shading images of the objects based on the proposed method. The reconstructed shape for a statue of head with the average shape of the databases provides an error evaluation, which is 2.6mm in average. This is sufficiently accurate for the future applications, such as on-line order-made of face-wearing products.

1 Introduction

3D shape information of human body has recently been applied to variety of applications. The shape of human body plays an important role for selecting the fitted size of human wears, such as clothes,, glasses, etc. Especially for the on-line e-commerce, the shape of personal body will be one of significant information for selecting the fitted size of wears. However, due to the high-cost of 3D scanners and the limit of measuring environment, it is still difficult for each customer to get the 3D shape information personally. If we can easily get 3D shape of the human body with normal cameras, we can select the fitted size in the easier manner with the on-line shopping. According to such motivation, we focus on the 3D shape reconstruction of human face from 2D images, which can be used for on-line order-made of face-wearing products, such as glasses.

Reconstruction of 3D shape of human face from 2D image is an attractive problem in the field of computer vision and computer graphics, because it can be used in many applications: face recognition, modeling, animation, virtual reality etc. Some methods to reconstruct 3D face shape from a number of images like video sequence are proposed [1][2]. The reconstruction accuracy is better than that reconstructed from only single image. Riaz et al.[3] reconstruct 3D face shape from several input images with projected parallel patterns. It can easily get pixel correspondence images, so that accurate reconstruction can be achieved. However, accurately calibrated projector and cameras are required, which is too expensive for personal use.

Shape from Shading[4] is a generally used method of 3D shape reconstruction from only a single image. From shading information of an input image, it estimates surface angle of object for light source and reconstruct 3D shape. Vetter at al.[5] presented a method to reconstruct shape and texture parameters of a 3D model from one image for face recognition. Hu at al.[6] reconstruct 3D shape by fitting a 2D vertex model to a single image. However, their method is used for recognition, so they don't provide accurate reconstruction that is sufficient for fitting of the wears.

In this paper, we propose a method to reconstruct 3D face shape from 3D anatomical database and a single shading image of a human face. According to the anatomical database of human heads, the shape from shading problem can be reduced to the parameter estimation problem of small number of eigenvalues taken by Principal Component Analysis (PCA) of the anatomical database. Therefore, we can obtain the face shape from only a single shading image. In addition to such computational effectiveness, the fact that the anatomical parameter can directly be estimated is also an important advantage of the proposed method since we can use the parameter for on-line order-made of face-wearing products, such as glasses.

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2 Method

First, we get eigenvectors from database by PCA, so that we can represent the shape of the faces by a small number of eigenvalues. Next, we synthesize the initial model image according to Lambert and Phong reflection model under perspective projection. We use averaged shape of the database as an initial model shape. By comparing shading information of the input image with that of the model image created from the database, the eigenvalues that represent the shape of the face are estimated and reconstructed 3D shape which represents.

2.1 Anatomical Database

Our database is normalized with the coordinate system decided by the orbitomeatal plane which includes both tragions and left orbitale. It consists of many anatomical important vertices. By reconstructing the shape based on the database, we can directly get important anatomical parameters of the input image. The organization of our database is as follows:

- 3D vertex information of 20's Japanese men.
- One sample consists of 430 vertices.

$$T = \{X_1, Y_1, Z_1, ..., X_{430}, Y_{430}, Z_{430}\}^T \quad (1)$$

- One sample has 830 triangular patch information.

When reconstruct a 3D shape, we use only face-part information (260 vertices, 485 patch information) and give four points(same as shown in Fig.1) on the input image for optimization cost.

2.2 Principal Component Analysis (PCA)

In this paper, we use PCA to obtain the representation of shapes of human faces with a small number of dimensions. To compute eigenvector P, we perform PCA on matrix $M = [T_1, T_2, \ldots, T_m]$ which consists of vertex vector of m people ($T_1 \sim T_m$).

Let $\bar{T}$ be average face shape of database, P_n be the matrix of the first n eigenvectors P attain 90 % contributing rate, A_n be the vector of the first n eigenvalues A, reconstructed 3D shape T' is as follows:

$$T' = \bar{T} + P_n \cdot A_n \quad (2)$$

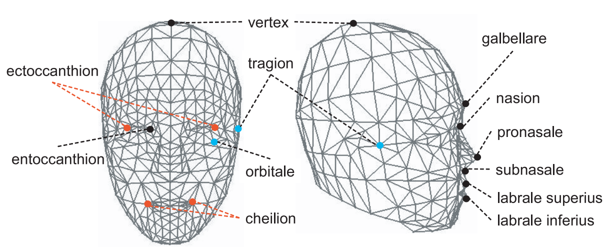

Figure 1. Anatomical Database. Red point is ectoccanthion and cheilion which used for optimization cost.

2.3 Reconstruction of 3D-face model

To reconstruct 3D shape of an input image, we have to make a model image in order to compare with the input image. The model image is a shading image of the face model made from 3D vertices and patch information of the database. To make the model image, it is important to estimate 6 parameters (3D position and pose to the camera plane) of the model correspond to the input image. Once position and pose is estimated, we can reconstruct the 3D shape of the input image represented by first n eigenvalues A_n. So to get the reconstructed shape, we estimate only $(n + 6)$ parameters instead of estimating all vertices. To get this $(n + 6)$ parameters, we optimize the model image with the input image by appropriating cost functions. We can get reconstructed shape of the input image by comparing shading information of the model image and the input image.

2.3.1 Model image

The camera with the point-light source is placed in front of the object face as shown in Fig.2.

We assume the perspective projection for the camera, but we assume that the distance of the point-light source is sufficiently large to approximate the parallel illumination. Applying Lambert and Phong reflection model to a model surface, the intensity of each patch is following:

$$I = I_{in}\left(K_a \cos\theta + K_b \cos^u \phi\right) \quad (3)$$

I_{in} is the intensity of incoming light, K_a, K_b is diffuse and specular reflectance of the face surface. u is directivity of reflectance. θ is the angle between the incoming light and the normal vector of an patch, ϕ is the angle between the reflected light and the line of sight. We decide I_{in}, K_a, K_b and u experimentally.

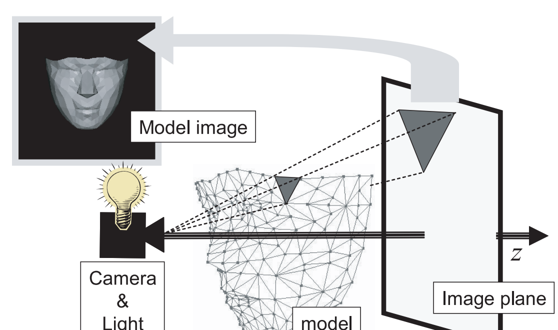

Figure 2. Basic concept of how to make model image.

2.3.2 Cost Function

We provide following two cost functions for optimization.

1. Normalized correlation C_e: Let normalized correlation among the input and model image be a cost function for optimization. Normalized correlation is a similarity of the shading information among the input and model image in the range of $1(maximum) > C_e > 0(minimum)$. $\bar{I}_i, \bar{I}_m$ are intensity of each pixels of the input and model image, I_i, I_m are average intensity of all pixels of the input and model image, N is all pixel number. Normalized correlation C_e is as follows:

$$C_e = \frac{\sum_{i=0}^{N-1}(I_i(i) - \bar{I}_i)(I_m(i) - \bar{I}_m)}{\sqrt{\sum_{i=0}^{N-1}(I_i(i) - \bar{I}_i)^2}\sqrt{\sum_{i=0}^{N-1}(I_m(i) - \bar{I}_m)^2}} \tag{4}$$

2. Range error of feature point C_f: Give four feature points manually on the input image and minimize the distance of feature point of the input and model image by optimization. Let $f_i(i)(i = 1, \ldots, 4)$, $f_m(i)(i = 1, \ldots, 4)$ be the feature points on the input and model image, C_f is as follows:

$$C_f = \sum_{i=1}^{4} |f_i(i) - f_m(i)| \tag{5}$$

Finally, we give following cost C for optimization. a, b are weighting factors, given experimentally.

$$C = a\,(1 - C_e) + bC_f \tag{6}$$

We minimize the cost C by using Downhill Simplex Method[7]. First, We set four feature points and set rough initial position in accordance with the input image and make a initial model image from the initial shape model of the database. To get the 3D position and pose of the model, we change position and pose and update model image to the direction of reducing the cost C. Once the position and the pose is estimated, we change the eigenvalues of the model to change model shape and update the model image. When the cost C converges by optimization, we get the final reconstructed 3D shape of the input image.

3 Experiments

For evaluating the effectiveness of the proposed method, we performed experiments to estimate the parameters of the face model from a single input shading images. Each image was a size of 256×256. We performed PCA on the matrix of vertex vectors of 52 people of the database, and used first 20 eigenvectors for reconstruction.

For accuracy evaluation of the reconstructed shape, we used the statue of head with known shape as input image. The statue has average shape of the database, and initial model shape was selected from the database randomly.

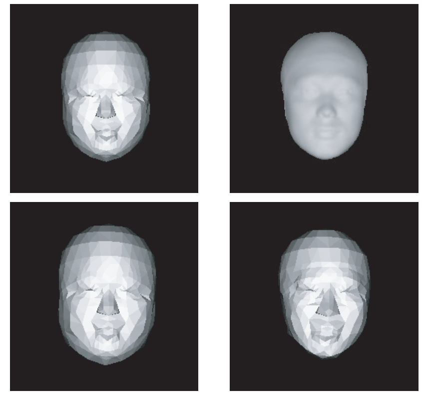

Figure 3. Shading image of the statue of head with average shape of the database. Top-left: Initial model image. Top-right: Input image. Bottom-left: After rotation and translation for the optimized model image. Bottom-right: Reconstructed image by our method.

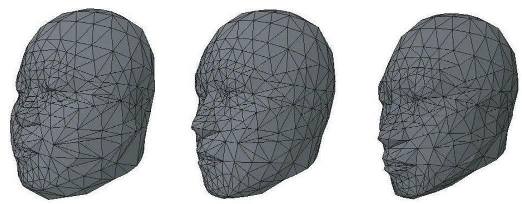

Figure 4. Synthesized novel view. Left: Novel view of initial model shape(Fig.3,top-left). Center: Average shape of the database(correct shape). Right: Reconstructed shape(Fig.3,bottom-right)

Fig.3(c),(d) shows the result image we can get by applying our algorithm on Fig.3(b). Fig.4 shows the novel views. Comparing init shape and reconstructed shape, the profile of the reconstructed model is closer to the actual model, especially on the areas such as jaw line and nose shape. Table.1 also shows the average distance error of all vertices and it's variances. We chose six samples as initial model shape from database randomly, and applied our algorithm on each samples. The vertex error is depend on the initial model shape, but decreased by the proposed method. We projected the vertex error of sample 6 onto input image in Fig.5. The errors are converging on every vertex.

Fig.6 shows a results of the input image of real human. The initial model image is the average shape of the database. The shading images shown in this figure indicate that our method can provide the reasonable shape accuracy. Fig.7 shows comparison with range data of target face. We get this data by Cartesia FACE SYSTEM of SPACE VISION[8]. By this scanner, we can get many 3D points of the target face. Assuming this data is correct data, we can

Table 1. Average error of all vertices(mm). Before: Initial shape. After: Reconstructed shape by our method

	average error		variance	
sample	before	after	before	after
1	7.65	3.65	39.37	9.33
2	2.19	2.11	2.21	2.03
3	3.85	2.40	6.52	3.80
4	3.01	2.12	5.35	2.24
5	4.67	2.90	11.24	5.68
6	4.43	2.57	12.16	3.65
average	4.30	2.63	–	–

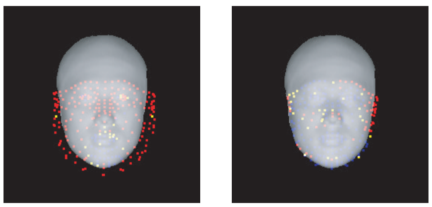

Figure 5. Error of re-projected vertices onto the input image. Left: Initial vertices. Right: Reconstructed vertices. Red means over 4 mm error from correct (average) shape, green means 3 to 4 mm, and blue means under 3 mm.

compare the accuracy between the initial model shape and the reconstructed shape by our method. As shown in Fig.7, the reconstructed shape closer to the correct shape than the initial shape.

4 Conclusion

We propose a method to reconstruct 3D face model from a single face-frontal shading image based on the original anatomical database. According to the anatomical database of human heads, the shape from shading problem can be reduced to the parameter estimation problem of small number of eigenvalues taken by Principal Component Analysis (PCA) of the anatomical database. We indicate that it is possible to reconstruct 3D face model with a close degree of accuracy to a 3D scanner. In addition, it is an important advantage that the anatomical parameter can directly be estimated since we can use the parameter for on-line order-made of face-wearing products, such as glasses.

Figure 6. Result image from real human face. Left: Initial model image. Center: Input image. Right: Reconstructed image by our method.

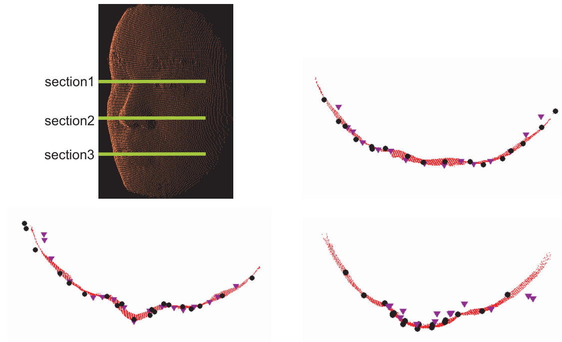

Figure 7. Comparison with range data of target face. Top-left: Range data(correct data). Top-Right: Section1. Bottom-left: Section2. Bottom-right: Section3. Red surface is the correct data, purple triangles are the initial model shape(average shape), black points are the reconstructed shape by our method.

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