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A 3D Face Coordinate System for Expression-Changed Pose Alignment

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Abstract

3D face data have been increased recently with the development of 3D data acquisition technology. 3D face has extensive applications. A proper coordinate system defined on faces is sometimes necessary. However, building a canonical coordinate system for all the 3D faces presenting the physiological vertical direction of human face is still an open question. In this paper, we propose a new 3D face canonical coordinate system based on the physiological structure of human face. Once locating the nose tip and finding the symmetry plane, we use the circular points on the face around the cheekbones to decide the front view, as the direction of the average normal of them is almost vertical to the center axis of human head. The experiment shows that our method is robust to rough data and provides a uniform description for all the 3D face models with different positions and expressions.

1. Introduction

As a natural biometric character providing good non-intrusiveness, face has a large number of applications, such as security, communication and entertainment. While 2D face recognition still encounters difficulties in handling large amounts of facial variations due to head poses and lighting conditions, 3D face recognition solves most of them by its explicit representation of facial surface. With the development of 3D data acquisition technology, many 3D face databases have been built, such as 3D-RMA, FRGC v2.0 [1], GavebDB [2], BU-3DFE and BJUT-3D Face Database. 3D face alignment and pose estimation is usually the first critical step for face recognition, facial behavior analysis and automatic model editing. Face pose determination is concerned with computation of the 3D face orientation and position. In computer animation, especially 3D virtual games, detection of a human face's position still has significant importance.

3D face canonical coordinate system has been studied to solve this problem. It does not only offer a solution to 3D face alignment but also provide a common base for 3D face pose estimation. Building a 3D face canonical coordinate system which is consistent with human visual habit and facial physiological structure has a significant importance to 3D face recognition and 3D face modeling. It also provides benefit for 3D face orientation and 3D face motion in 3D face animation.

PCA (Principal Components Analysis) is the original method [3,4]. It tries to identify the 3 primary directions of maximum variation in 3D face data as the x, y and z axis in 3D space. If the 3D face data includes errors such as noise or partial missing, the coordinates may be changed. Wu et al. [5] decides a canonical coordinate system by finding the symmetric plane of facial surface and detecting two fiducial points, nose tip and nose base. However, the direction determined by the two fiducial points does not show the physiological vertical direction of our face, for different people have high or low noses. Hu et al. [6] fits a cylinder by face data to build the coordinates. But the coordinates will also be changed when human facial expression changes. ICP (Iterated Closest Point) [7,8,9,10]is a 3D face alignment method, especially for fine alignment. But ICP based approaches usually require a good initialization and can't offer a uniform coordinate system for all the 3D face models. McCool et al.[11], Conde et al.[12], Sun Yi and Yin Lijun[13] build 3D face canonical coordinate system with the help of feature points around eyes, such as the inside eye point and the outside eye point. However, the 3D face data we get is often coarse, the preprocessing work like filling and smoothing takes time and blurs the real feature points around eyes.

In this paper, we propose a human physiological structure based 3D face canonical coordinate system. After locating the nose tip and finding the symmetry plane, we use the circular points on the face around the cheekbones to decide the second axis. The anatomy of human head shows that the face around the cheekbones is nearly the

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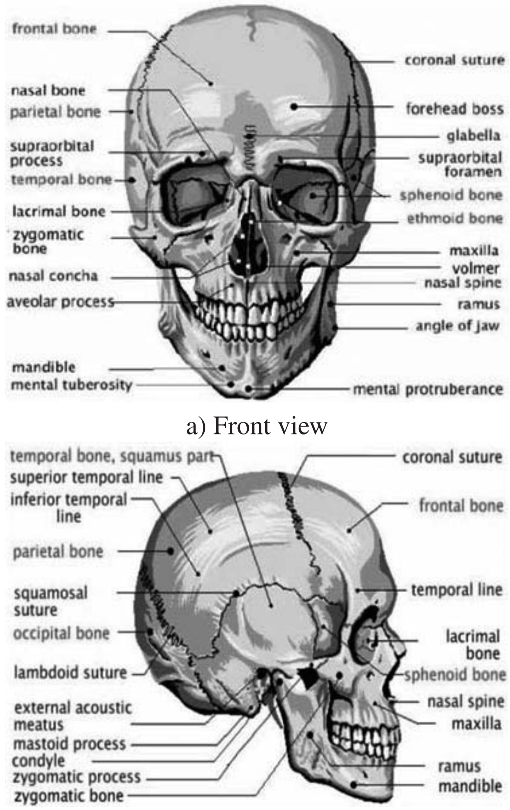


a) Front view

b) Side view

Figure 1. Structure of human skull [15]

same among different expressions and we deduce that it can be used to decide the upright face orientation. Considering the disadvantage of feature-based approaches that they rely on accurate 3D faces, we compare various discrete methods for computing circular points and finally use a normal fitting based method to estimate second-order differential components. It is robust to coarse data which has artifacts, noise and missing pixels. As there are many circular points on the surface, we propose a distance constraint to extract the ones around the cheekbones. This 3D face canonical coordinate system offers a uniform coordinates for all the 3D faces with different expression, which is suit for human visual habit and can be applied to various 3D face data.It is also helpful for 3D face alignment and 3D face recognition.

2. Physiological Structure of Human Face

Human face is composed of skull, muscle and skin, including subcutaneous tissue and hair of surface [14]. Skull decides the overall appearance of facial outline. Muscle attaches on the skull, and its movement brings various expression and motion of faces. Skin is very elastic, presenting the external subtle character of faces.

Craniofacial skull is composed of 15 bones, the front down part of skull, as shown in Figure 1. At both sides of the nasal cavity, above the mouth, there are two mandibles. Outside these two mandibles, there are two diamond-shaped cheekbones.

The muscles on human face are skeletal muscles, attached to human skull and human face skin. They can be classified into two kinds by their function, masticatory muscles and facial muscles (facial expression muscles). Masticatory muscles produce movement of face such as closing mouth and opening mouth. Facial muscles are inside face skin, most start from the skill surface and the fascia, and end at face skin. When facial muscles contract, the skin and organs on the face can also be pulled and produce various expressions, such as happiness, sadness and angst.

Although each part of a human face is independent of the others, but some study shows that there are some relationships among them. A human face is nearly symmetrical. When people change facial expression, facial surface is similar to isometric transformation. On the zygomatic surface of human face, there is a region similar to spherical surface, some differential components of which do not change under different expressions. The point in this region is called circular point of which the maximum and minimum principal curvatures are almost the same. We can deduce form anatomy that the average normal of the circular points is almost vertical to the center axis of human head, and can be used to decide the upright view of a human face. All these mentioned above provide the proof for us to build the human physiological structure based 3D face canonical coordinate system.

3. Outline of Our Method

As mentioned above, we use the circular points to decide one axis of our 3D face canonical coordinate system. Suppose Z axis corresponding to the upright direction of the face (not look-up or look-down), X axis corresponding to the front direction of the face (not turn left or turn right), and Y axis corresponding to the width direction of the face as Figure 2 shown.

First, extract the symmetrical plane and the nose tip of a face. Then the origin of canonical coordinate system is located by the nose tip. As the symmetrical plane has been found, the normal of this plane decides one axis of canonical coordinate system, the Y axis. Second, find the circular points around cheekbones and compute the average normal of them. As there are many circular points on the surface, we use distance restriction to extract the right circular points around cheekbones. For the average normal of circular points shows front direction of the face, it's to be used as another axis of canonical coordinate system, the X axis. When this axis is fixed, the face will not look upward nor downward, but directly forward. Finally, the Z axis can be done by cross product the X axis and the Y axis with

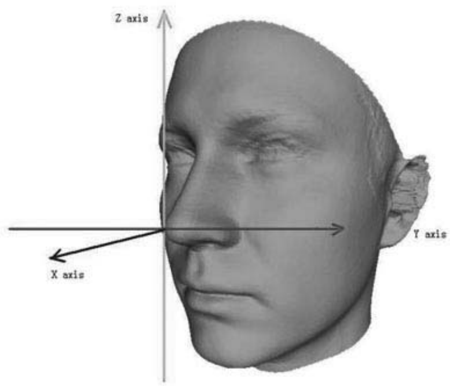


Figure 2. Definition of our x, y and z axis

right-hand rule.

4. Extract Symmetrical Plane and Nose Tip of Human Face

As the estimation of the symmetrical plane and the nose tip is a wide studied problem, there are many methods have been proposed [5,16,17]. Compare their performance and the condition they need, we use the method proposed by Wu et al.[5]. This method is robust to coarse data and carried out effectively.

4.1. Symmetrical Plane Detection

Suppose the points set of a human face mesh M is:

$$V_M = \{p_i \in R^3 | 1 \leq i \leq N\} \quad (1)$$

For an arbitrary plane, we can find the mirror of V_M:

$$V_M^m = \{p_i^m \in R^3 | 1 \leq i \leq N\} \quad (2)$$

The point p_i in V_M is symmetrical to point p_i^m in V_M^m. Once we align the two sets accurately, segment $p_i p_i^m$ must be vertical to the true symmetry plane and its central point must lie on it. That is the segment $p_i p_i^m$determines the true symmetry plane. Then the intrinsic point set of the true symmetry plane can be shown as follows,

$$A = \{x | < x - (p_i + p_i^{m'})/2, p_i - p_i^{m'} >= 0, 1 \leq i \leq N\} \quad (3)$$

where$< \cdot, \cdot >$is the cross product.

We use ICP to align V_M and $V_M^{m'}$, which is widely used for geometric alignment of 3D models. However, to ensure the convergence of ICP, a rough alignment of the initial position is required. So we need to choose the initial symmetry plane carefully. Here we use PCA to solve this problem. Considering error from 3D data acquisition and non-exact-symmetry of facial surface, actually we solve A for each point in facial surface and then perform least-mean-square method for final solution.

4.2. Nose Tip Detection

We compute the intersection of symmetric plane and the 3D face mesh to get the central profile. The nose tip is located on the central profile. Let C denotes the central profile curve extracted, l_e denotes the line through both end points of the curve C. The nose tip is a point on the curve C, with the maximum distance to the line l_e. We can also locate the nose tip by its curvature.

After extracting the symmetric plane and the nose tip, we find the origin and one axis of our 3D face canonical coordinate system.

5. Circular Points Extraction and Front View Determination

5.1. Definition of Circular Points in Differential Geometry

In differential geometry, let $\mathbf{r} = \mathbf{r}(u, v)$ be a regular parametrization of surface S in R^3, where $\mathbf{r}$ is a smooth vector valued function of two variables. It is common to denote the partial derivatives of $\mathbf{r}$ with respect to u and v by $\mathbf{r}_u$ and $\mathbf{r}_v$.

The parametrization thus defines a field of unit normal vectors: $\mathbf{n} = \frac{\mathbf{r}_u \times \mathbf{r}_v}{|\mathbf{r}_u \times \mathbf{r}_v|}$.

The first fundamental form completely describes the metric properties of a surface. Its formula is: $I = ds^2 = Edu^2 + 2Fdudv + Gdv^2$. The coefficients E, F, G can be found by taking the dot product of the partial derivatives. $E = \mathbf{r}_u \cdot \mathbf{r}_u$, $F = \mathbf{r}_u \cdot \mathbf{r}_v$, $G = \mathbf{r}_v \cdot \mathbf{r}_v$.

The second fundamental form is usually written as $II = Ldu^2 + 2Mdudv + Ndv^2$. The coefficients L, M, N can be computed with the aid of the dot product as follows: $L = \mathbf{r}_{uu} \cdot \mathbf{n}$, $M = \mathbf{r}_{uv} \cdot \mathbf{n}$, $N = \mathbf{r}_{vv} \cdot \mathbf{n}$.

Then the normal curvature is

$$K_n = L(\frac{du}{ds})^2 + 2M\frac{du}{ds}\frac{dv}{ds} + N(\frac{dv}{ds})^2, n \in N \quad (4)$$

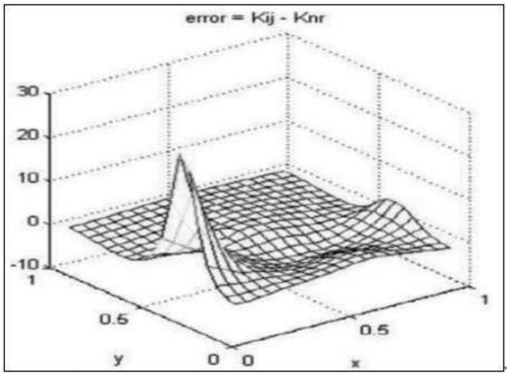
Taking all possible tangent vectors then the maximum and minimum values of the normal curvature at a point are called the principal curvatures, K_1 and K_2. The circular point is defined as the point where $K_1 = K_2 \neq 0$ or $\frac{L}{E} = \frac{M}{F} = \frac{N}{G} \neq 0$.

In this paper, we use the definition $K_1 = K_2 \neq 0$ to extract circular point.

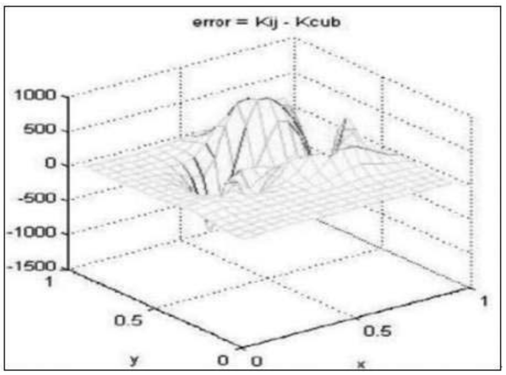
5.2. Circular Point Calculation

There are many methods to compute the second order differential components. We experiment three classical methods [18,19,20] and found that the method proposed by Cheng performed best as Figure 3 shown. So we choose it to extract the circular points in this paper.

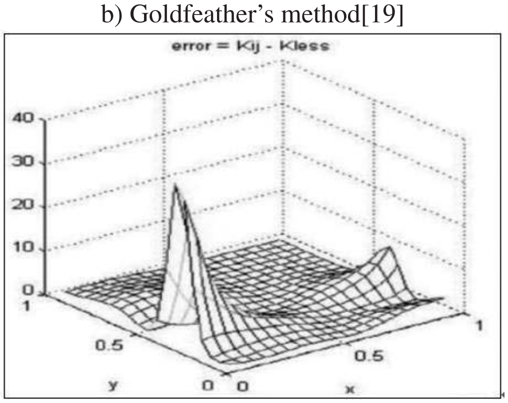
This method takes into account the normal information of all neighboring points and does not rely on the accuracy



a) Cheng's method [18]



b) Goldfeather's method[19]



c) Stokely's method [20]

Figure 3. The error between the real Gaussian Curvature and the estimated value by three classical methods.

of the normal vector at that point. Compared with the state-of-the-art methods for estimating curvatures, this approach is shown to be more accurate and robust for noisy data.

Steps are as follows:

1. Fit normal vectors based on Taylor expansion, replace the original normal vectors by the new normal vectors and iterate the fitting process until get the robust normal vectors with their partial derivatives.

For a point p on surface $\mathbf{r}(u,v) = (u,v,f(u,v))$, the neighborhood is chosen as the points neighboring p in a sphere with fixed radius. The unit normal vector $\mathbf{n}(u,v) = (X,Y,Z)$in this neighborhood is continuous. Its Taylor expansions with its first-two components are:

$$X(u,v) = \mu_1 + w_{11}u + w_{12}v + o(u^2+v^2) \quad (5)$$

$$Y(u,v) = \mu_2 + w_{21}u + w_{22}v + o(u^2+v^2) \quad (6)$$

where $\mu_1 = X(0,0)$, $\mu_2 = Y(0,0)$, $w_{11} = X_u(0,0)$, $w_{12} = X_v(0,0)$, $w_{21} = Y_u(0,0)$, $w_{22} = Y_v(0,0)$.

Let p to be the origin, the original unit normal vector of p as Z axis, creating a unit vector vertical to the original normal with some rule as Y axis, we build the local coordinate system at p. The points in the neighborhood of p under this system have the coordinates $(u_i, v_i, f(u_i,v_i))$ and the corresponding normal coordinates $(X_i,Y_i,Z_i)(Z_i > 0)$. Then the objective function for optimal normal fitting based on first-order Taylor expansion is:

$$\min \sum_i (\mu_1 + w_{11}u_i + w_{12}v_i - X_i)^2 + (\mu_2 + w_{21}u_i + w_{22}v_i - Y_i)^2 \quad (7)$$

$$s.t. \mu_1\mu_2 w_{11} - (1-\mu_2^2)w_{12} + (1-\mu_1^2)w_{21} - \mu_1\mu_2 w_{22} = 0$$

It can be divided into two independent linear systems

$$\min \sum_i (\mu_1 + w_{11}u_i + w_{12}v_i - X_i)^2 \quad (8)$$

$$\min \sum_i (\mu_2 + w_{21}u_i + w_{22}v_i - Y_i)^2 \quad (9)$$

Each of them is as the form as $\min_{\mu} ||A\mu - B||_2^2$ and we use $\mu = (A^TA)^{-1}A^TB$ to solve these two systems respectively. Finally we get the first two components and corresponding partial derivatives of p's normal vector.

2. For every point on the surface, use the first two components and corresponding partial derivatives of its normal vector to compute the value of K_1 and K_2.

1) For every point calculate the Weingarten matrix W

$$W = -\begin{pmatrix} X_u & X_v \\ Y_u & Y_v \end{pmatrix} \quad (10)$$

2) Calculate the eigenvalue λ_1, λ_2 ($\lambda_1 \geq \lambda_2$) of W, and then $K_1 = \lambda_1$, $K_2 = \lambda_2$.

3. Extract circular points.

For every point, if its $K_1 = K_2 \neq 0$, the point is extracted as the circular point.

5.3. Front View Determination

As mentioned in section 2, there are circular points in the cheekbone regions and the direction of the average normal of them is almost vertical to the center axis of human head, which can be used to decide the front view of human face. But there are also some circular points which are not in the cheekbone regions, such as the points around the nose tip, the points on the forehead. Here we propose a distance constraint method to avoid these.

The circular points in the cheekbone regions must be keeping a certain distance from the nose tip and symmetric plane, and they are symmetrical for the symmetric plane. At the same time, we get rid of the small regions with few circular points which are noisy on the surface. Through these post-processing, we get the circular points in the cheekbone regions and calculate the average normal of these points as the front view axis of our 3d face canonical coordinate system.

6. Experiments

Here we use the 3D face data from the GavabDB database [2]. The 3D face models consist of laser range scan from 61 subjects. Each has several scans with different positions and expressions, such as ”look-up”, ”look-down”, ”smile” and ”laugh”. First we translate and rotate these models as we don’t know any information about their coordinate systems. After we find the nose tip, we use it as the origin to define a sphere, then we cut the original data with the sphere, leaving alone the region only we interested in at the final results.

Figure 4 is the results of our experiment with 6 typical models. There are four rows and each row forms a group. The first row is the original models, six 3D face models of three people, each with two scans including position change and expression difference. The second row is the results of symmetric planes and nose tips with each model. The third row is the results of circular points with our method. And the last row is the final 3D face canonical coordinate system of each model with our method. Compared to the PCA method, which is sensitive to the noise and dose not have physiology meaning, the 3D face canonical coordinate system proposed in this paper is robust to expression-changed noisy 3D face models and consistent to human face physiological structure.

7. Conclusions

In this paper, we have proposed a new 3D face canonical coordinate system based on human physiological structures. This 3D face canonical coordinate system offers a uniform coordinates for all 3D faces through different expressions. It is consistent to human visual habit and can be applied to rough 3d face data. It does not only offer a solution to 3D face alignment but also provide a good help for face orientation and face motion in face animation.

However, as people’s appearance varies extensively, not only the different person with fat face or thin face but also the same person with different ages, the extraction of circular points in the cheekbone areas is not correct sometimes. Improving our method or finding more robust computing method should be done in our future work.

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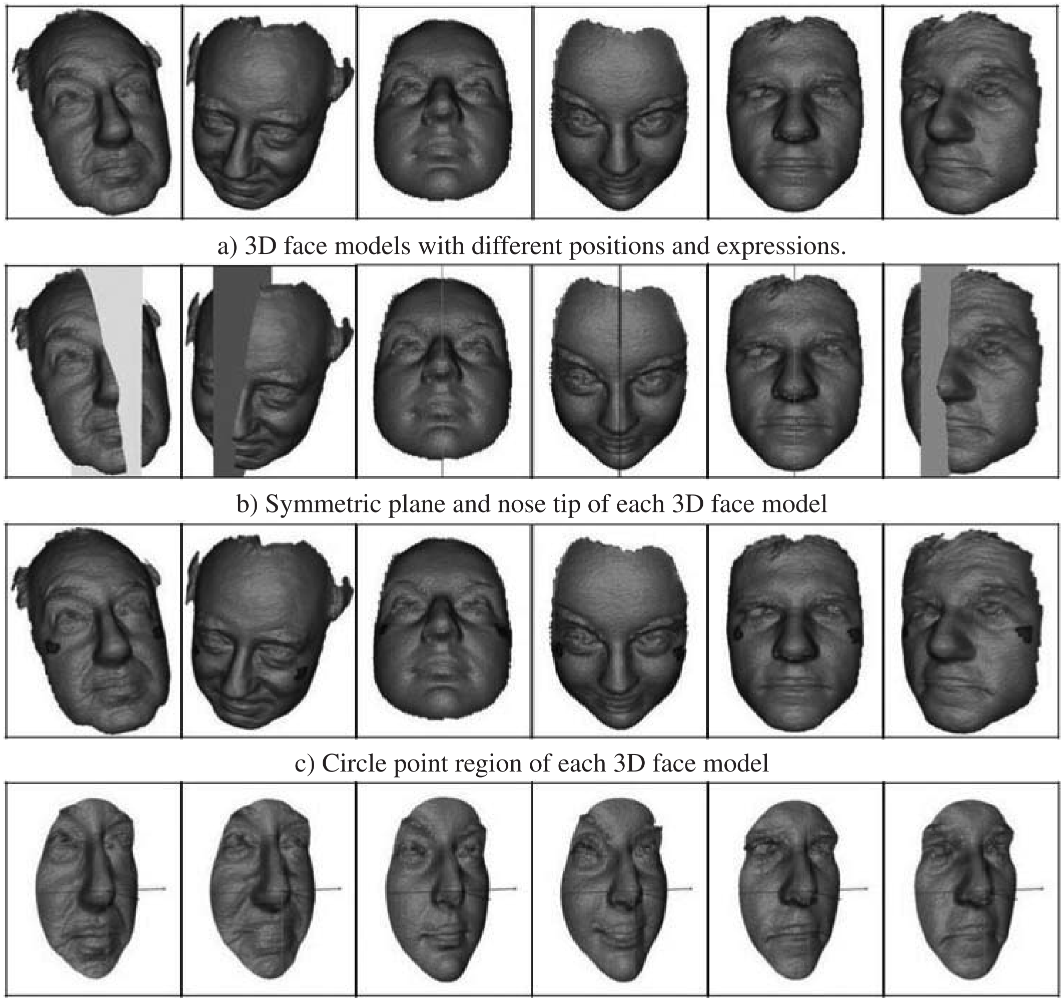

a) 3D face models with different positions and expressions.

b) Symmetric plane and nose tip of each 3D face model

c) Circle point region of each 3D face model

d) The final 3D face canonical coordinate system of each 3D face model with our method

Figure 4. 6 typical outputs of our experiments.

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