A NOVEL TEMPLATE HUMAN FACE MODEL WITH TEXTURING

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Abstract: We present a method to fit a template face model to 3D scan face. We first normalize the size and align the orientation then fit the model roughly by scattered interpolation method. Secondly we run the optimization method based on Allen's work. We are able to generate face models which have ”poin-to-point” correspondence among them. We also suggest a way to transfer any facial texture image over this fitted model.

1 INTRODUCTION

Creating realistic 3D human face is a difficult task. Since human face has very complex geometry, and its difference between races and ages is large. Although 3D human face model has been created for many application, it can be said that there is no standard way of making human face model from scratch. Making a realistic human face is still a challenging task. Related study have been reported to create morphable or animatable human face from 3D face scan, however there are still many known or unknown issues relating human face model (Ekman and V.Friesen, 1975) (Parke, 1972).

In this paper, we propose a method for creating face model which has full correspondence among different faces. By having such a model with full correspondence, it becomes an easy task to animate face with known parameters among different face models. With this model, it becomes a trivial task to group face by comparing the corresponding geometry or morphing between different faces. It would also be possible to use this face model to recognize human face if the quality of created face model improves more.

The main contribution of this paper is a template-based face registration technique for establishing a point-to-point correspondence among a set of face model. Our method of creating such a face model is based on the Allen's work (Allen et al., 2003). Starting from the 3D scan face data, we try to fit our template face to those scan data with as less as human interactions intervened. The fitting process runs semi-automatic except that facial markers have to be marked by human at first. We describe our fitting method from a template face to any 3D-face scan taken from real human in this paper. We also suggest one method of transferring facial image over this face model.

2 RELATED WORK

Blantz and Vetter (Blanz and Vetter, 2003) create a morphable face model by taking images of several faces using a 3D scanner and putting them into ”one-to-one” correspondence by expressing each shape using the same mesh structure. Using the morphable model, it is possible to group changes in vertex position together for representing common changes in shape among several surfaces. Using principal component analysis, they succeeded to find a basis for expressing shape changes between faces.

Concept of morphable model face model has been extended by many researchers. For instance Vlasic (Vlasic et al., 2005) published a method for expressing changes in face shape using a multi linear model, accounting for shape changes not only based on a person's identity but also based on various expression.

Model with full correspondence is also studied by Praun and co-workers work (Praun et al., 2001). In order to establish full correspondences between models, they create a base domain which is shared between models, then apply a consistent parameterization. They search for topologically equivalent patch boundaries to create base domain mesh. Since our

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domain is limited to only Human face model, a base domain would be prepared in advance.

3 OVERVIEW

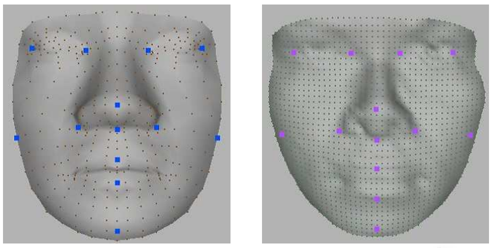
The task of the template face model fitting is to adapt a model face to fit an individual's 3-D scan face. As input to this process, we took several 3D face scan with Vivid700 (MINOLTA, 1999). We created the template face model with a commercial modeling software. Our template face contains 435 vertices and 822 triangles. Boundary of the shape is the contour of face. We first crop the 3D scan data outside of the face contour. We preprocess the surfaces so that the shape of boundary of template face model and 3D scan face is almost the same. However this is not a strict demand, but doing so makes the fitting result better empirically. Our fitting method are comprised of two part. We first fit the template face model roughly by using scattered interpolation method, then refine the fitting by minimizing the error energy function which describes the quality of the match. For visual richness of 3D surface especially for facial expression, texturing is very important topic. We suggest a method of transferring any facial textual image over the fitted model with full correspondence among them.

4 3D SURFACE FITTING

If the two face model's shapes differ substantially, optimization framework could stuck in local minima and will not result in desirable face model. So our method first fit the template face model roughly by using scattered data interpolation, then use the optimization framework suggested by Allen (Allen et al., 2003). This way makes our fitting process more robust than (Allen et al., 2003). Before starting fitting, we normalize the size of each model by resizing the bounding box of its model and align the center of the model. Scattered data interpolation is described in 4.1, and optimization framework is described in 4.2.

4.1 Scattered Data Interpolation

We first locate the same number of facial feature points on both on template face model and 3D scan face data manually. The number of marker points is 13 in our case. Once we have set markers which have one-to-one correspondence between template face and 3D scan face, we construct a smooth interpolation function that gives the 3D displacements between the 3D scan face and the new adapted position for every vertex in the template face model.



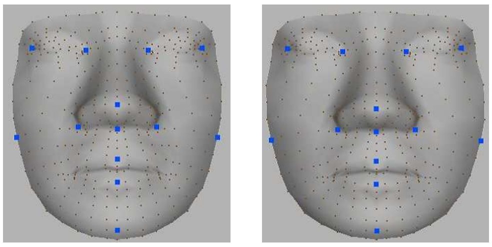
(a) (b)

Figure 1: Facial markers. (a) Facial markers v_i on template face. (b) Facial markers m_i on 3D scan face.

Given a set of known displacements $u_i = v_i - m_i$ away from the 3D scan face positions at every marker position i, construct a function that gives the displacement u_j for every non-constrained vertex j in the template face model. We use a method based on radial basis functions, that is the function of the form

$$f(v) = \sum_i c_i \phi(\| v - v_i \|) + Mv + t \qquad (1)$$

where $\phi(r)$ are radially symmetric basis functions. M and t are affine components. To determine the coefficient c_i and the affine components M and t, we solve a set of linear equations that include the interpolation constraints $u_i = f(v_i)$, as well as the constraints $\sum c_i = 0$ and $\sum c_i v_i^T = 0$, which remove affine contribution from the radial basis functions. Many different functions for $\phi(r)$ have been proposed. We have chosen $\phi(r) = |r|^2 \log(|r|)$ for our function. We have applied this interpolation for each coordinate, X, Y, and Z.



(a) (b)

Figure 2: Scattered data interpolation. (a) Original template face. (b) Template face after RBF interpolation.

4.2 Model Data Fitting Optimization

After fitting roughly by scattered interpolation method described above. We improve the quality of fitting by minimizing the fitting error metric by adapting Allen's method (Allen et al., 2003). We describe this method for fitting template face model to 3D scan face. Each vertex v_i in the template surface is influenced by a 3x4 affine transformation matrix T_i. We try to find a set of transformations that move all of the points in the template face to 3D scan face surface.

The quality of the match is evaluated using a set of error functions: data error, smoothness error, and marker error. These error terms are described in the following sections.

Marker error. Equal number of Facial feature points are placed on both the template face and the 3D scan face at the locations which are characteristic for faces. About 13-20 features markers are suffice to locate facial feature locations. We call the 3D location of the markers on the 3D scan face $m_{1\dots m}$, and the corresponding vertex index of markers on the template face $t_{1\dots m}$. The marker error term E_m minimizes the distance between each marker's location on the template face and the 3D scan face:

$$E_m = \sum_{i=1}^{m} \parallel T_{t_i} v_{t_i} - m_i \parallel^2 \quad (2)$$

Data error. We fit the marker first, then fit all the remaining points in the template face. We define a data error term E_d as the sum of the squared distances between each vertex in the template face and the 3D scan face surface.

$$E_d = \sum_{i=1}^{n} \delta_i dist^2(T_i v_i, D) \quad (3)$$

where n is the number of vertices in template face, δ_i is a weighting term to control the validity of the match, and the $dist()$ function computes the distance to the closest point on the 3D face scan. If the surface normals at the corresponding points are more than $90°$, set δ_i to 0 otherwise set to 1.

Smoothness error. Allen (Allen et al., 2003) suggested that simply moving each vertex in the template face to its closest point in the 3D scan separately will not result in a well arranged mesh, because neighboring parts of the template face could be mapped to disparate parts of the 3D scan face. To constraint the problem, we adopted the smoothness error, E_s (Allen et al., 2003). we formulate the constraint between every two points that are adjacent in the template face:

$$E_s = \sum_{\{i,j|\{v_i,v_j\}\in edges(T)\}} \parallel T_i - T_j \parallel_F^2 \quad (4)$$

where $\parallel \cdot \parallel$ is the Frobenius norm. By minimizing E_s we prevent adjacent parts of the template face from begin mapped to disparate parts of the 3D scan face.

Combining each error. Our complete objective function E is the weighed sum of the three error functions above:

$$E = \alpha E_m + \beta E_d + \gamma E_s \quad (5)$$

where the weights α, β, and γ are adjusted to guide the optimization. We use a quasi-Newtonian solver, L-BFGS-B (Zhu et al., 1994).

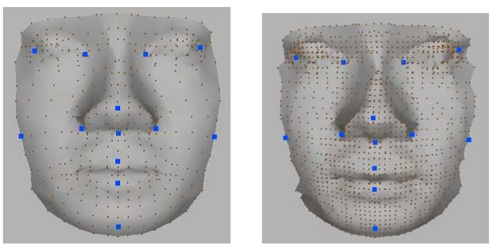
We first run the optimization using the relatively low resolution mesh of the template face compared with the 3D scan face. After that we subdivide the resulting template face by inserting a new vertex between every edges of the mesh. Newly inserted vertex position and its affine transformation is interpolated between the two vertices of the edge.

We vary the weights, α, β, and γ, so that marker point fits first then the remaining vertice move to the appropriate position so that overall surface of the template face fit to the 3D scan face. We run our optimization as following

At the first stage (Low resolution of the template face)
1. Fit the markers first: α=10, β=1, γ=1
2. Make the data error term to dominate: α = 1, β=10, γ=1

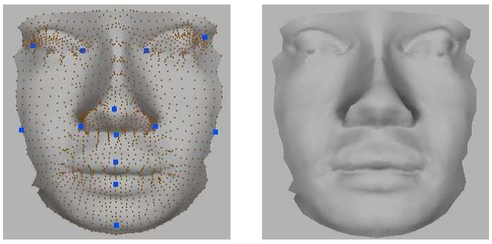
At the second stage (High resolution of the template face)
1. Continue the optimization: α=5, β=1, γ=0
2. Make the data error term to dominate: α = 0, β=10, γ=1

Template face after fitting sometimes have ripple over high curvature area. We have applied laplacian smoothing (Taubin, 1995) to this surface and get more smooth surface as seen in Fig 4.



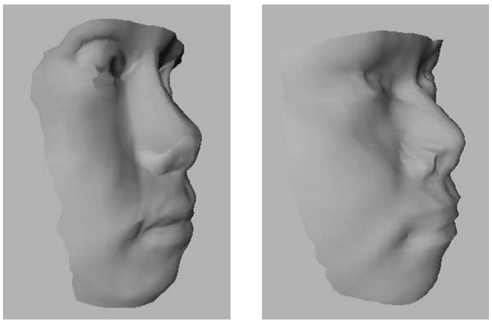
(a) (b)

Figure 3: Fitting template face. (a) Template face after fitting to 3D face scan. (b) Subdivided template face after fitting.



(a) (b)

Figure 4: (a)Smoothing face model after fitting. (b) display in shading mode.



(a) (b)

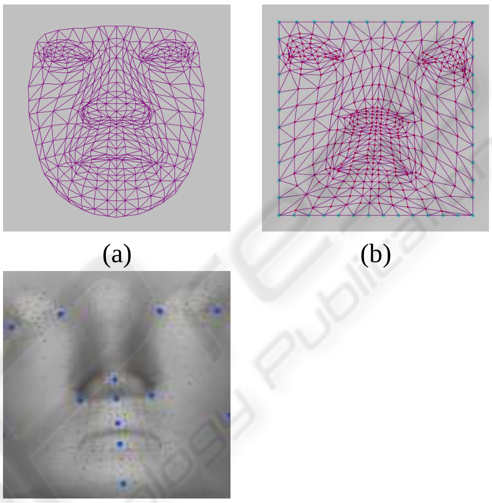
Figure 5: (a)Fitted template face from another angle. (b) Target 3D face scan from the same angle.

5 CONSTRAINED FACIAL TEXTURE MAPPING

We propose a method based on radial basis function (RBF) technique to apply a facial texture image to our template based 3D face model. Fist we calculate the mapping from 3D template face surface to 2D parameter space. With this mapping we obtain the template face image. Then user specifically assigns the corresponding 2D points in the sample facial image to those points in the template face image. We employ RBF to morph the sample face image with the constraint of these feature points. Our method is characteristic in that we do not re-calculate the 2D mapping parameter for each face model, but use the common parameterization prepared in-advance with the morphed face image.

5.1 Template Face Image

Texture mapping or parameterization of 3D mesh is to compute a mapping between a discrete surface patch and an isomorphic planner mesh through a piecewise linear mapping. This piecewise linear mapping is simply defined by assigning each mesh node a pair of coordinate (u,v) referring to its position on the planer region. A number of work on parameterization has been published, and almost all techniques explicitly aim at producing least-distorted parameterization. We employ the intrinsic parameterizations (Desbrun et al., 2002) for our parameterization method. Summary of the intrinsic parameterization is described in Appendix. Fig 6 shows the result when we apply this parameterization to our template face model. We call the resulting 2D image the template face image.



(a) (b)

(c)

Figure 6: (a)3D template face. (b) 2D parameterization. (c) template face image.

5.2 Face Image Morphing

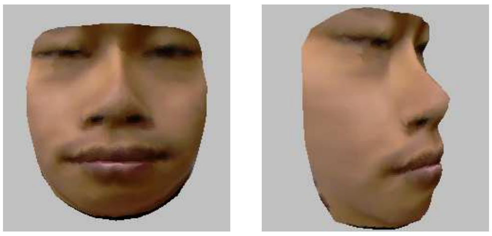
2D image Morphing method we employ is basically same as 4.1. The energy-minimization characteristic of RBF ensures that the mapping function smoothly interpolates constraints with non-deformation properties. User manually assign corresponding 2D points in the sample texture image. User can set an arbitrary set of constrained points, although for simplicity this could be the same set of facial feature points as we use in 4.1. The morphing result is in Fig 7. We transform this morphed face image over the face model after fitting in Fig 8. Fig 9 shows various texture image applied to our template face model.

6 CONCLUSIONS

We have succeeded to make face models which have full point correspondence among them by fitting the generic template face model to each 3D face scan. Although initially it requires human interaction to locate facial feature markers on each model, fitting process

(a) (b)

Figure 7: Locate facial feature points int the original texture image which correspond to the facial feature points of the template face image in Fig 6 (c). We then apply RBF based image morphing with the constrained feature points. (a)original texture image. (b) morphed texture image.



(a) (b)

Figure 8: Texture mapping after fitting. (a)textured face model. (b) view from another angle.

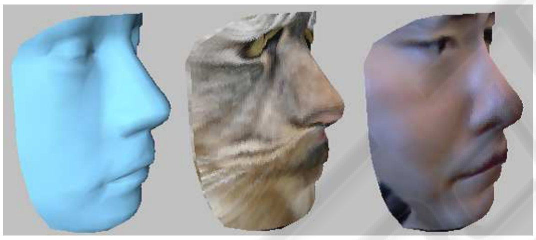


Figure 9: Various texture mapping to template face model.

proceeds automatically. The resulting face model is nicely fitted to the target 3D scan face. Although the fitted face surface sometime is not as smooth as we desire, we can smooth the surface by using laplacian smoothing method without blurring the facial feature points. Since our template face is created by ad-hoc method, it calls for the way to create a ideal template face. Praun et al (Praun et al., 2001) create a base domain model by tracing patch boundaries to represent overall shape of the model. Although created base domain is too abstract for our template model, it could be generated from its base domain. In stead of using a triangular mesh, several studies have been made to fit a spline surface over dense polygon mesh or points. Besides of the patch boundary issue relating to spline surfaces, it is a more suitable model for animation and provide a fine but more expensive model for rendering.

Since we have a face model with consistent parameterization, it is a simple application to morph between any two faces. Although our face model after fitting looks very similar to the original scan face, we haven't evaluated how accurate the fitting is. One possible method is to construct a graph which consists of geodesic paths between every pair of the facial marker points. The accuracy of the fitting could be done by comparing these graphs.

We suggested one method to map texture image over our template based face model. With this method user doesn't have to adjust texture coordinate for each different face model, but rather morph the image with the constraint of matched feature points between the template face image and itself. For the restricted domain as human face model this method was found to produce pleasing result.

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APPENDIX

Parameterization of 3D mesh is to compute a mapping between a discrete surface patch and an isomorphic planar mesh with least distortion. Desbrun at el (Desbrun et al., 2002) describe a general distortion measure E, which is given by Dirichlet Energy E_A and Chi Energy E_χ

$$E = \lambda E_A + \mu E_\chi$$

where λ and μ are two arbitrary real constants.

$$E_A = \sum_{edges \in (i,j)} cot\alpha_{ij} |u_i - u_j|^2$$

where $|u_i - u_j|$ is the length of the edge(i, j) in the parameter domain, and α_{ij} is the opposite left angle in 3D as shown in Fig 10.

$$E_\chi = \sum_{j \in N(i)} \frac{(cot\gamma_{ij} + cot\delta_{ij})}{|x_i - x_j|^2} (u_i - u_j)^2$$

where the angles γ_{ij} and δ_{ij} are define in Fig 10.

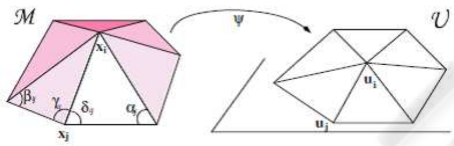

Figure 10: 3D 1-ring and its associated flattened version.

Since the gradient of E is linear, computing a parameterization reduces to solving the following sparse linear system:

$$MU = \begin{bmatrix} \lambda M^A & + & \mu M^\chi \\ 0 & & I \end{bmatrix} \begin{bmatrix} U^{internal} \\ U^{boundary} \end{bmatrix} = \begin{bmatrix} 0 \\ C^{boundary} \end{bmatrix} = C$$

where U is the vector of 2D-coordinates to solve for. C is a vector of boundary conditions that contains the positions where the boundary vertices are placed. M^A and M^χ are sparse matrices where coefficients are given respectively by:

$$M^A_{ij} = \begin{cases} \cot(\alpha_{ij}) + \cot(\beta_{ij}) & \text{if } j \in N(i) \\ -\sum_{k \in N(i)} M^A_{ik} & \text{if } i = j \\ 0 & \text{otherwise,} \end{cases}$$

$$M^\chi_{ij} = \begin{cases} (\cot(\gamma_{ij}) + \cot(\delta_{ij}))/|x_i - xj|^2 & \text{if } j \in N(i) \\ -\sum_{k \in N(i)} M^\chi_{ik} & \text{if } i = j \\ 0 & \text{otherwise,} \end{cases}$$