Craniofacial Reconstruction Based on MLS Deformation

Li Jiang, Xiangyin Ma, Yaolei Lin, Lewei Yu, Qianwei Ye
College of Computer Science and Technology
Zhejiang University of Technology
Zhejiang Hangzhou
CHINA
jl@zjut.edu.cn

Abstract: Craniofacial reconstruction aims at estimating the facial outlook associated to an unknown specimen. Craniofacial reconstruction is generally based on the statistical tissue thickness on anthropometric landmarks. However, the features points alone are not enough for realistic reconstruction. So, in our paper, we take advantage of a reference facial model, through measuring the differences between the target facial feature points and the reference facial feature points, a novel craniofacial reconstruction algorithm based on moving least squares deformation is presented. The 3D skull mesh model is obtained with Marching Cube Algorithm, which extract the iso-surfaces from a complete head CT slices datum. The holes detected in the 3D skull model can be repaired with different methods after the holes are clarified. Then, the craniofacial is reconstructed using MLS deformation with the constraint of a reference facial model. The experimental results show that the methods can produce more desirable results than others'.

Key-Words: Craniofacial reconstruction, Deformation, MLS, Feature points, Hole repairing

1 Introduction

Cranio-Facial Reconstruction (CFR) is an essential processing phase in the fields of forensics, anthropology as well as maxillofacial surgery. It is widely used in the identification of an unknown body. In forensic science, facial models need to be reconstructed from victims' skulls for identification. In paleo-anthropology, facial models need to be reconstructed to give us a visual image when skulls of prehistoric people are found. The facial reconstruction can also be used in medicine, such as surgery planning. The goals of forensics, anthropology and maxillofacial surgery differ substantially. However, the mathematical basis of computer-aided cranio-facial reconstruction is effectively the same.

The traditional facial reconstruction process relies on tedious manual work, and the operation is directly imposed onto the original skulls, which may cause invertible harm. The progress in computer science and the improvement of medical imaging technologies during recent years has significant repercussions on this domain. Numerous research groups in universities and institutes have pursued computer-aided CFR research, e.g. University of Washington, Sheffield University, and Waseda University[1][2][3]. However, one of the major problems in reconstructing facial models is how to achieve a high level of realism with high efficiency.

The surface fitting techniques have been used as a main approach in many computer aided reconstruction systems. In such systems, the tissue thickness constraints are used at facial landmarks to control the generic facial model adaptation. However, the landmark set is far less than enough to control the facial geometry. In our paper, we take advantage of a reference facial model to serve as the constraints, and choose Moving Least square (MLS) to perform the deformation due to its property of high smoothness. Besides that, we have studied the hole repairing algorithm, and repair them accordingly using distinct method. Our method could get the target face model with high realism by modifying only one reference face model.

2 Related works

3D annual methods for craniofacial reconstructions have been developed and are currently used in practice. Manual reconstruction methods require a lot of anatomical and artistic modeling expertise and are, as a result, highly subjective. Computer-aided methods, on the other hand, are consistent and objective. Moreover, these methods can be executed in a short time and output multiple reconstructions from the same skull using different modeling assumptions(older, fatter,…).

Craniofacial reconstruction is generally based on the statistical tissue thickness on anthropometric landmarks. The interpolation based on feature points only considers the relationship between the feature points on the skull to be reconstructed , so the reconstruction result is not realistic enough. Furthermore, no one can determine which of these feature points should be taken to produce the best result. Some techniques [4][5]fit a facial template to the endpoints of a set of virtual dowels positioned on a 3D digitized model of the target skull. The dowel lengths represent average tissue depths at a limited number of predefined cephalometric landmarks. Other techniques deform a 3D reference skull to a target skull based on the crest lines[6], anatomical landmarks[7], features points[8] or distance map representation[9]. The calculated skull deformation is then spatially extrapolated and applied to the skin surface associated to the reference skull. Our approach goes into the facial template deformation category, so we continue to talk more about these methods.

Based on a reference model, the deformation obtains the final skin surface by warping the model template [10]. The key issue for this category of method is the selection of the deformation function. Currently, many computer-aided craniofacial reconstruction methods deform the model in partitions, or using RBF (Radial Basic Function). But the final result is not very desirable.

Giuseppe et al.[11] use spiral CT to obtain the model of skull which needs to be reconstructed, and a deformation matrix is established according to a series of feature points which are marked correspondingly between the obtained skull and a reference skull. The final facial model can then be acquired through interpolation.

Instead of using a single reference data, Vanezis et al. [4] choose to establish a database of reference facial models. By analyzing using anthropological knowledge, they successfully select a reference skull, which is the most similar to the current skull in anthropological information, together with its corresponding facial model. Finally , facial model template is adjusted to fit the feature points to the ones on the skull which needs to be reconstructed.

Khler et al. [12] mark some feature points on the skull model according to the ratio of the skull and the depth of the soft tissue. Then the RBF interpolation is used to generate the human head. The experiment results show that this method reconstructs the face model quickly, and is able to adjust some individual facial characters. But its realistic has not been proved yet.

Claes et al. [13] adopted the alterable model based on statistics. Their statistical model is constructed from a database consisted of 118 independent facial models, and limits the reconstructions to statistically plausible outlooks. The reconstruction is obtained by fitting the model skull feature points to the corresponding feature points indicated on a digital copy of the skull to be reconstructed. The fitting process changes the face-specific statistical model parameters in a regularized way and interpolates the remaining feature points fitting error using a minimal bending thin-plate spline (TPS)-based deformation.

In fact, our craniofacial reconstruction method is totally based on 3D model, so it turns out to be a face model deformation problem. Now there are plenty of ways available to realize the mesh deformation problem. Free-form deformation (FFD) [14] is widely used in commercial software today. In FFD, a control shape is predefined in terms of a certain structure, then the shape is deformed by adjusting the control points of this predefined structure. However, FFD has not taken into account the features of the control mesh, and its operation tends to be complicated. Noh et al. [15] present an approach to achieve localized real-time deformations of polygonal models using Radial Basis Functions (RBFs). Animations are produced by controlling an arbitrary sparse set of control points defined on or near the surface of the model. But the result is not smooth enough. Igarashi et al. [16] present a method that produce as-rigid-as possible transformations by minimizing the distortion of 2D triangular elements. Such techniques have been successfully used in the shape-preservation 3D mesh deformation, and the context of image deformation presented by Kun et al. [17]. However, it needs to solve a linear system as large as the vertices mount which is time costing. Sundaraj [18] uses volume conservation and Pascal's Principle to simulate soft tissue deformation, while it does little work related to the craniofacial reconstruction.

Inspired by the property of high smoothness of Moving Least square (MLS), we adopt it as the deformation function. This method doesn't need to divide the model into partitions. It computes the control range through weight function and weight radius. Since all the feature points have taken part in the computing process, the smoothness of the reconstruction could also been ensured. In other words, this method can fully satisfy our requirements.

3 Craniofacial Model Reconstruction Based On MLS Deformation

3.1 Algorithm Overview

We depict the algorithm flow in figure 1. Firstly, the skull model and its corresponding facial surface are obtained using CT scanning. Typically the skull mesh model contains holes due to disqualified scans or standard long-term damage (especially in the soft-bone area around the nose). The holes are filled to guarantee consistency among the reference facial model and the source skull model. Secondly, we mark feature points on the source skull model, and get the corresponding feature points on the target facial model through mapping. Finally, a MLS deformation is adopted to reconstruct the facial model. Each procedure will be explained in detail in the next sections.

3.2 Data Preparation

Before facial reconstruction, a number of original skull models must be obtained. We acquire the 3D digital model of skull directly using 3D scanners.

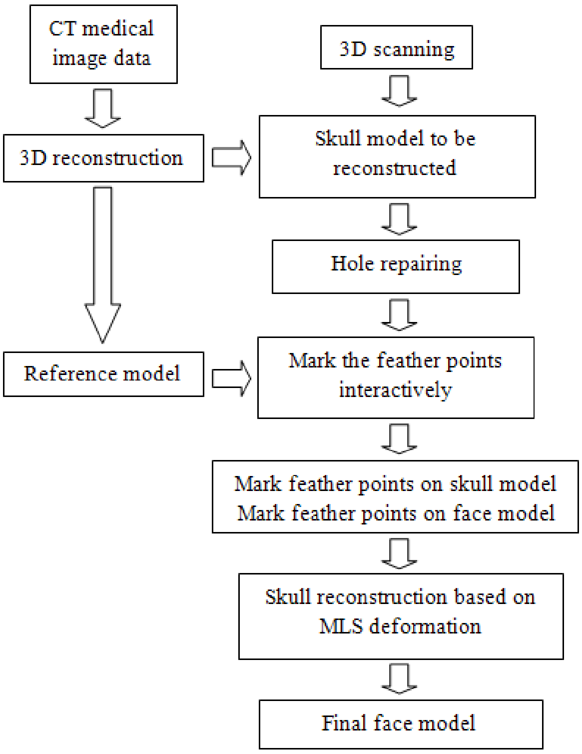


Fig.1: The Algorithm Flow of Craniofacial Model Reconstruction Based on MLS

With a complete head CT slices as source data, the iso-surfaces are extracted using Marching Cube algorithm for getting the corresponding facial model as a reference facial model. Usually, the skull we collected has a certain degree of damage. So the damaged skull must be repaired first in the preprocessing stage.

After getting the complete skull model, the thickness data of soft tissue is needed to reconstruct the skull. In addition, we also obtain a standard reference model as the deformation template before the reconstruction. With the collection of soft and hard tissue data, we mark feature points on the reference face model and perform the deformation. The positions of feature points and the thickness of soft tissue we adopted are referred to Yuwen Lan's statistical data [19]. Figure 2 shows the models and the feature points on the skull model.

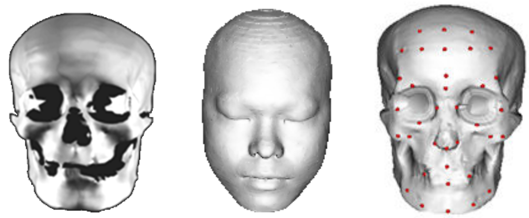


Fig 2. (left) Original skull model. (middle) reference facial model. (right) skull to be reconstructed and its feature points

3.2.1 Hole Repairing in the Three-Dimensional Skull Model

The captured skull models often incomplete due to various factors. The holes, such as eye sockets and zygomas, contained in the model will affect the marking of feature points, as all feature points must be marked on the surface of the model. If there is a hole existed, the feather point on it would have an error which would seriously affect the following deformation. Therefore, it is essential to repair the holes in the skull model. But the skull model is complex and diverse, so no unified method existed would suit for repairing holes in our case. Thus, we classify the holes detected, and repair them accordingly using distinct methods [20].

For the general holes, the intuitive repairing method would produce a good result. Firstly, discrete points are inserted and triangulated into the holes. Then, we create implicit surface in the holes and adjust these discrete points. Finally, the mesh is smoothed. Here, the creation of hole implicit surface and the mesh smoothing have to solve the matching problem between the repaired grid and the surface surrounding the holes. This method is hence appropriate for the complicated holes in the irregular region. We utilize this hole repairing algorithm as a basic approach, and use it to handle general holes and complicated holes in irregular region.

However, as to big holes, it is usually impossible to control the shape only with the points around the hole. We propose a novel algorithm advancing layer-wise solution (ALS) to deal with this situation. In our means, the role for the points around the hole is to capture the local shape of the adjacent area and generate the initial implicit surface. Then we take the following steps interatiely until the holes have been acceptably repaired:

1.Adjust the current insertion point *p* to implicit surface S, which is denoted as *p'*.

2.Add *p'* as the additional constrained point, recalculate implicit surface together with the previous constrained points and get new implicit surface *S'*.

3. Denote the insertion point *p'* as *p*, and *S'* as *S*.

4. Iterate steps 1-3 until all the insertion points are adjusted.

Our ALS method improves the standard FHRA for large size holes, and guarantee that all the insertion points and the points around the hole lie on the same implicit surface. The comparisons are displayed in Fig.3. It shows that the ALS method outperforms the FHRA results and is capable to produce a realistic output.

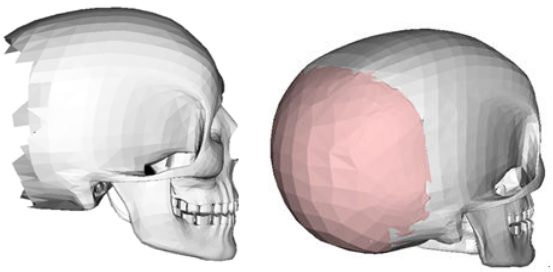


Fig 3. (a) Source skull model (b) Our ALS method

3.2.2 Feature Points Marking

Craniofacial reconstruction aims at estimating the facial outlook associated to an unknown skull specimen. Estimation is effective based on tabulated average values of soft tissue thickness measured at a sparse set of landmarks on the skull. Current computerized techniques mimic the landmark interpolation procedure using a single facial surface template. These landmarks, or skull feature points, refer to the points that are meaningful in the geometry or anatomy, and easy to be located in the skull surface.

Taking advantage of these points, we are able to uniquely identify individuals and meet the needs of reconstruction of three-dimensional human face. Thus, in the setting of the skull feature points set, our paper set the corresponding facial feature points according to a 3D craniofacial reconstruction indicator system[19], which is built especially for Chinese people. This indicator system is established using X-ray photography and computer 3D scanning ranging method. We mark 28 feature points as basic feature set, both on the 3D skull model and reference model. In addition, 14 feature points is added as supplementary feature points to make results more accurate. These 42 landmarks are indicated on the skull in Fig. 4.

Craniofacial feature points are the facial surface points corresponding to the skull feature points, between them the soft tissue are filled. So the problem here is how we can precisely match the skull feature points with the reference craniofacial feature points. Rodrigues extracts the feature points automatically by using a 2D image [21]. Inspired by his idea, we only need to mark feature points on the reference facial model manually. By adjusting both of the two models' position, these feature points are mapped onto the skull model automatically through orthogonal projection.

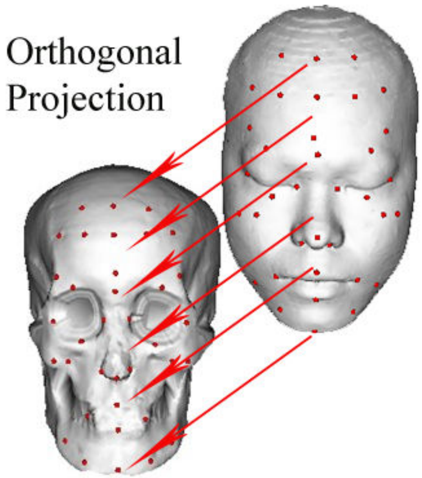


Fig 4. Mapping feature points to skull model through orthogonal projection

The dowel lengths of features points represent average of ancestry-, gender- and age-matched tissue depths at a limited number of predefined cephalometric landmarks. Soft tissue thickness can then be regarded as the length of normal at the skull control point of the skull surfaces. In our approach, the corresponding craniofacial feature points are calculated automatically by taking advantage of the tissue thickness along the normal direction. Suppose $P(x_0,y_0,z_0)$ is one of the skull control point, $N(n_x,n_y,n_z)$ is its normal direction, *h* is the soft tissue thickness at point *p*, $Q(x, y, z)$ is craniofacial control point corresponding to the point *p*, and can be calculated by the following equations:

$$x = x_0 + \frac{n_x}{\sqrt{n_x^2 + n_y^2 + n_z^2}} \times h$$

$$y = y_0 + \frac{n_y}{\sqrt{n_x^2 + n_y^2 + n_z^2}} \times h$$

$$z = z_0 + \frac{n_z}{\sqrt{n_x^2 + n_y^2 + n_z^2}} \times h \quad (1)$$

The selection of landmark points or skull features is used to deform the model towards a given target skull. A facial template is then fitted to the endpoints of this set of virtual dowels positioned the 3D digitized model. There is no direct correlation, however, between the reported tissue depths and the associated skin surface shape of an individual. So, in the next section, we will show how to get enough constraints from a reference model for the realistic craniofacial reconstruction.

3.3 Craniofacial Reconstruction base on MLS Deformation

In order to reconstruct the skull face accurately and quickly, we use the reference facial model as constraint and reconstruct the original face of the skull. It is essentially a deformation from the reference facial model to the target facial model. We mark the feature points onto the skull model and get the corresponding facial points, then mark corresponding feature points interactively on the reference facial model. After that, the reference facial model is deformed for matching the feature points to their corresponding feature points on the source skull model. As a result, the target face of the source skull model is formed.

3.3.1 Fitting problem definition

Our facial template for craniofacial reconstruction consists of a combination of two sets of three dimensional point coordinates (P^{ref}, Q^{fea}), with $P^{ref} = \{p^{ref}_j \mid j = 1.....N\}$ a dense point set representing the facial surface of the reference model, and $Q^{fea} = \{q^{fea}_i \mid i = 1......L\}$ representing the set of model landmark or feature points(skull landmarks, thickness dowel ends, e.g), where typically N>>L. These L feature points are regarded as handles for deformation.

The craniofacial reconstruction of a face F now consists of estimating the dense set of facial surface point coordinates F^s based on a model P^{ref} and a set of correspongding landmark points Q^{fea} on the model and target skull. One way to estimate F^s is to determine a smooth mapping or deformation T : $R^3 \rightarrow R^3$ satisfying the interpolation conditions at the landmark points.

So the problem is given the position of feature points and all the vertex contained in the 3D mesh, how can we calculate the new position *p'* of mesh points which are located at *p* when the feature points are moved from p_i to a new position p_i' ($0 \leq i \leq L$,). Note that, the displacement of given feature points $\Delta p_i = p_i' - p_i$ equals to 0 if the point is not moved. The key problem is to calculate the displacement for each mesh point Δp_j, j = 1….N.

On one hand, we hope that the deformation is totally based on the feature points, while on the other hand, the local features of the reference model are wished to be preserved. since the free-form deformation is really complex, we use scattered data interpolation to deform the reference face model. Currently, scattered data interpolation method which is widely used includes radial basis function method and moving least squares method. Radial basis function interpolation deformation method is a global-based method. Its local effect is poor.

Thus, an as-rigid-as possible deformation is appreciated. The concept of as-rigid-as-possible transformation is first introduced by Alexa et al.[22] in the context of image morphing. Igarashi et al. [16] apply the idea in the context of 2d shape manipulation. They triangulate the input image and solve a linear system whose size is equal to the number of vertices in the triangulation. Because of the need to solve a global system, they report that their method somewhat slow when there are 300 vertices on a 1 GHz machine. In contrast, Schaefer et al. [Schaefer et al. 2006], performs image deformation by solving a small 2x2 linear system locally at each grid point. Zhu et al. extends Schaefer's work to the 3d setting. So in this paper, moving least squares method is adopted and a craniofacial reconstruction method based on MLS is proposed. In the next section, we will describe moving least squares method briefly [23][24] .

3.3.2 Affine deformation

The MLS is one of many different surface-reconstruction techniques. The technique is attractive since the surface is reconstructed by local computations and it generates a surface that is smooth everywhere.

Let p_i be a set of feature points and q_i be the new positions of them. The key idea of moving least squares method is to find the best affine transformation $T_v(p_i)$ that minimizes

$$E = \min \sum_i w_i \left| T_v(p_i) - q_i \right| \quad (2)$$

where p_i and q_i are composed with three dimensions (x, y, z). w_i is weight function, *R* is effect radius. The nearer the distance from v to p_i, the less the value of weight function is.

Let deformation function be $f(v)=T_v(v)$, $T_v(v)$ is an affine deformation function, consisting of two parts: a rotation transformation matrix *M* and a translation *T*.

$$T\,T_v(v) = xM + T \quad (3)$$

The translation transformation can be rewritten as

$$T = q^* - p^* M \quad (4)$$

where p^* and q^* are weighted centroids given by equation 5.

$$p^* = \frac{\sum_{i=1}^{n} \omega_i p_i}{\sum_{i=1}^{n} \omega_i}, \qquad q^* = \frac{\sum_{i=1}^{n} \omega_i q_i}{\sum_{i=1}^{n} \omega_i} \quad (5)$$

Then $T_v(v)$ can be rewritten as

$$T_v(v) = (v - p^*)M + q^* \quad (6)$$

and equation 2 can be rewritten as

$$E = \min \sum_i w_i \left| \tilde{p}_i M - \tilde{q}_i \right| \quad (7)$$

where $\tilde{p}_i = p_i - p^*$ and $\tilde{q}_i = q_i - q^*$.

Finding an affine deformation that minimizes equation 7 is straightforward , by using the classic normal equations solution.

$$M = (\sum_{i=1}^{n} \tilde{p}_i^T w_i \tilde{p}_i)^{-1} \sum_{j=1}^{n} w_j \tilde{p}_j^T \tilde{q}_j \quad (8)$$

The deformation function $f(v)$ is then

$$f(v) = (v - p^*)(\sum_{i=1}^{n} \tilde{p}_i^T w_i \tilde{p}_i)^{-1} \sum_{j=1}^{n} w_j \tilde{p}_j^T \tilde{q}_j + q^* \quad (9)$$

We usually select spline function as the deformation function. According to the latest MLS review [16], the result is better when the following weight function is used.

$$w(x) = \begin{cases} (1-x)^4(1+x) & (0 =< x <= 1) \\ 0 & (x > 1 \text{或} x < 0) \end{cases} \quad (11)$$

So we select equation 11 as the deformation function in this paper.

3.3.3 Rigid deformation

While affine transformations contain effects such as non-uniform scaling and shear, many objects in reality do not undergo even these simple transformations. In order to make the deformation as rigid as possible, the matrix M in equation (3) should be an orthogonal matrix and satisfy the following condition:

$$M^T M = I \quad (12)$$

Let $\theta_i = \omega_i(x)^{1/2}$, $P = \theta_i(\tilde{p}_1 \cdots \tilde{p}_N)$, $Q = \theta_i(\tilde{q}_1 \cdots \tilde{q}_N)$ (P and Q are 3 by N matrices). Then equation (7) could be rewritten as

$$E = \min \sum_i \left| M(\theta_i \tilde{p}_i) - \theta_i \tilde{q}_i \right|^2 = \left\| MP - Q \right\|_F$$
$$= tr((MP-Q)^t (MP-Q))$$
$$= tr(P^t P) + tr(Q^t Q) - 2tr(Q^t MP)$$

where $\|\cdot\|_F$ is the Frobenius norm. Since P and Q are constant, minimizing E corresponds to maximizing $\lambda = tr(Q^t MP) = tr(MPQ^t)$. Note that PQ^t has a singular value decomposition $PQ^t = U\Lambda V^t$ such that $\Lambda = diag(\lambda_1, \lambda_2, \lambda_3)$ is diagonal with non-negative entries, and U , V are orthogonal. Thus

$$\lambda = tr(MU\Lambda V^t) = tr(MU\Lambda V^t)$$

λ is maximized when $M = VU^t$

In summary, we need to calculate M. First calculate P and perform singular value decomposition on

$$PQ^t = \sum_i \omega_i(x) \left| (\tilde{p}_i - p^*)(\tilde{q}_i - q^*) \right| = U\Lambda V^t$$

Then $M = VU^t$ is easy to get.

In summary, craniofacial reconstruction based on MLS rigid deformation can be described as the following steps.

- Mark the feature points on the skull and calculate the corresponding facial feature points

First, according to skull feature points defined by Lan[19], we mark feature points on the source skull model as the primary feature points, and a certain number of auxiliary feature points if needed. When all skull feature points are determined, we need to mark reference face feature points at corresponding positions on the reference face model.

For each control point i, the position on the reference facial model is marked by p_i, and the position of facial control point associated with skull control point on the source skull model is marked by q_i. And q_i is calculated by $q_i = s_i + d_i$, where s_i is the position of source skull control point, d_i is the depth of soft tissue associated with s_i. This equation means that facial control point associated with skull control point is calculated the surface normal of this control point plus the depth of soft tissue.

- Take moving least squares function $f(p)$ meeting $q_i=f(p_i)$ as the deformation function.
- Solve the target deformation function using MLS rigid deformation method, and then the reconstruction is finished.

3.3.4 Additional reconstruction hints

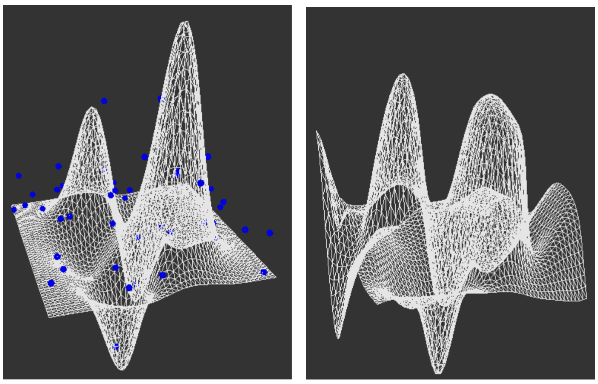
The tissue depth values at the feature points define the basic shape of the reconstructed face, assuming depth measurements being always strictly orthogonal to the skull surface. That is to say, each landmark is associated with a vector in surface normal direction, corresponding to the typical direction of thickness measurement. However, this assumption is not always valid. Some skull/skin correspondences are in fact non-orthogonal to the skull surface, especially in the area of the lips. This should be corrected for at a later step of the fitting process.

For feature points marking, more rules are expressed by the placement of vertical and horizontal guides in a frontal view of the skull. From this user input, the placement of a few features points, around the lips, is adjusted. The updated landmark set is used to compute another deforming function, which deforms the pre-fitted head model in the adjusted regions.

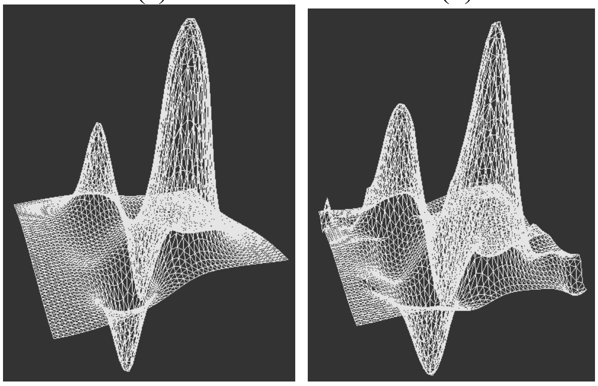
4 Experimental results and discussions

For digitalization of a skull computed tomography(CT) may be used as one modality. In our experiment the source skull data is obtained from a hospital's CT data. Our algorithms have been implemented in VC++ with the Visualization toolkit. The experimental environment is core 2 T5450 with 1.66 GHz main frequency of CPU and 1.5GB memory.

To prove the effectiveness of our craniofacial reconstruction method, the comparison of RBF deformation and MLS deformation results are shown in Figure 5. Figure 5(a) shows the original surface on which 100 feature points are placed as constraint points. The blue points are the target positions where the feature points will move to. Figure 3 (b) shows the result using RBF deformation, and Figure 3 (c) shows the result using MLS deformation.



(a) (b)



(c) (d)

Fig 5. the comparisons of results between RBF and MLS deformation. (a) original surface and target points. (b) RBF deformation. (c) MLS affine deformation. (d) MLS rigid deformation.

As seen from the experiment results of the three methods, we find that RBF method make the grid change too much even don't reserve the main frame of the grid. That's because RBF method considers the all distances from the feature points to the current point. It may bring about great variation of a point that ought to have little or no movement of resulting in fluctuation in the whole deformation. Thereby the accuracy of the deformation is decreased. Due to the weight function and the effect radius, MLS affine deformation could make the grid more smooth. Although it's result is smooth, but it don't make sure the feature points standing on the grid. So it would lost the grid's detail. In contrast, MLS rigid deformation's result is the most gratifying. It not only hold the main shape of the grid, but also make the feature points stand on the final grid so that it can preserve the grid's details.

We use all these three methods to reconstruct the same skull model from the reference facial model. Figure 4 is the result of these three methods. We can find that the craniofacial reconstruction which is based on RBF deformation has unexpected effect in detail, because this method takes the whole model into consideration. The RBF deformation in one feature point is constraint by the all feature points on

Table 1 efficiency of MLS and RBF reconstruction method

	Number of points of the mesh	Number of feature points	Time Consume(/ms)		
			RBF deformation	MLS affine deformation	MLS rigid deformation
Surface Deformation	2601	100	32	39	30
Craniofacial Reconstruction	265749	36	1045	1281	1211

the model. It considers the distance between the current feature point and all the other feature points, and then calculates the distance to obtain a deformation function. While towards the facial model, deformation in one feature point may only be affected by the feature points around it and the feature points far away from it can't affect it. The MLS affine method is based on the least squares method, and weight function is used to control fitted area. We can see from the Figure 4. In comparison with the RBF method, the final result match the skull more accurately. But it only find the best affine transformation to fit the facial model to the skull without making the feature points standing on the final model exactly. It exchanges the details for the smoothness. After comparing the three result, the MLS rigid method's result is the most accurate. In other words, this method has a good deformation in detail

The two experiments prove the feasibility of the MLS deformation method. This paper leads the MLS deformation to the craniofacial reconstruction, and present a reconstruction method based on MLS deformation.

To display the efficiency of the algorithm, table 1 shows the time cost of our algorithm, which is compared with the RBF deformation method. In the process of MLS deformation reconstruction, set the k=4,d=18.2.

According to the result of our experiments and analysis, this method has the following characteristics:

(1) MLS deformation reconstruction method has a good effect in detail

(2) In the efficiency of the algorithm, MLS deformation reconstruction method is similar to RBF deformation reconstruction.

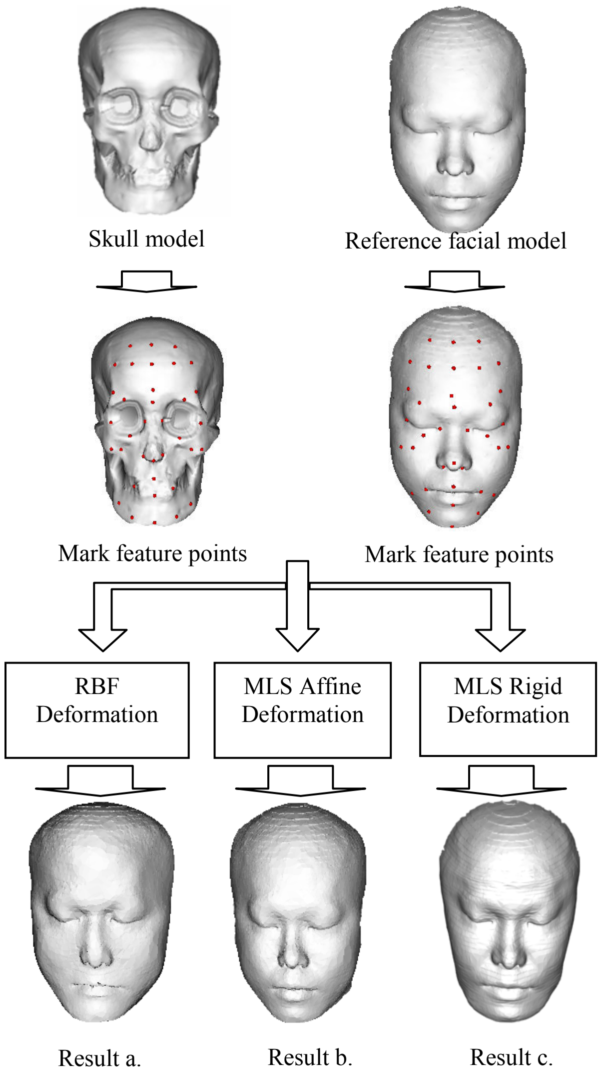


Fig 6. Facial reconstruction using three different methods.

5 Conclusions and Future Work

Craniofacial reconstruction aims at estimating the facial outlook associated to an unknown skull specimen. In order to eliminate the template-related bias and to minimize the unrealistic character of the reconstructions caused by large model deformation, a craniofacial reconstruction method based on MLS is proposed in his paper. The traditional moving least squares deformation method is improved and introduced into the craniofacial reconstruction.

The main idea of our algorithm is to fit a facial template to the endpoints of a set of virtual dowels positioned on a 3D digitized model of the target skull. Using the source skull and the reference facial model as the experiment data, through measuring the differences between the target facial feature points and the reference facial feature points, we can calculate the deformation function which is based on the improved MLS. Then we get the target face through deforming the reference face model. As the experimental results show, the reconstructed three-dimension human facial model is accurate and efficient.

But there are still many weaknesses in our implementation of reconstruction algorithm, so the next step of our study will focus on the following aspects:

(1) The establishment of model database. In this paper, only one standard head model is used as the reference model and deformed for reconstruction. In order to make the reconstruction result closer to the appearance of the dead, model database need be established, and the models should be stored classifiably, so the basic information can be extracted more conveniently according to the basic data .

(2) The study of deformation method based on MLS. Since only the affine transformation function is selected as the fitting function in this paper, there are probably some problems in implementation process, such as the matrix is not invertible and can't be solved. Therefore, the detailed deformation method should be studied and improved in the future.

(3) The verification problem of reconstruction result. Since there is no quite objective method to verify the reconstructed facial model, therefore, a more objective verification method is hoped to be established in the future. The photos of the dead will be used to analyze our reconstruction result qualitatively and quantitatively in our future study.

Acknowledgements

This work was partly supported by the Zhejiang Province Natural Science Foundation under grant No.Y1080383 ,No.Y1090335 and No. Z1090630, and key project from Education Department of Zhejiang Province under grant No.20070192.

References:

[1] Greef S D, Willems G. Three-dimensional craniofacial reconstruction in forensic identification. Latest progress and new tendencies in the 21st century. J.Forensic Sci., 2005, 50 (1): 12-17.

[2] Iscan M Y. Global anthropology in the 21st century. Forensic Sci Int, 2001, 117: 1-6.

[3] Stephan C N. Anthropological facial "reconstruction"—recognizing the fallacies, "unembracing" the errors, and realizing method limits. Sci Justice, 2003, 4(2):193-200.

[4] Vanezis P, Vanezis M, Mecombe G, et al. Facial reconstruction using 3D computer graphics. Forensic Science International, 2000, 108: 81-95.

[5] J.Muller, A. Mang, T. Buzug, A template-deformation method for facial reproduction, in Proceedings of the Fourth International Synposium on Image and Signal Processing and Analysis—ISPA2005, pp. 359-364, 2005

[6] G. Quatrehomme, A fully three-dimensional method forfacial reconstruction based on deformable models, Forensic Sci. 42, pp. 649-652, 1997.

[7] L. A. Nelson, S.D. Michael, The application of volumn deformation to three-dimentional facial reconstruction: a comparison with previous techniques, Forensic Sci. 94, pp. 167-181, 1998.

[8] M. W. Jones, Facial reconstruction using volumetric data, in proceddings of the Sixth International Vision Modelling and Visualization Conference—VMV-01, pp. 135-150, 2001.

[9] D. Vandermeulen, P. Claes, P. Sutens, S. De Greef, G. Willems, Volumetric deformation face models for cranio-facial reconstruction, in Proceedings of the Fourth International Synposium on Image and Signal Processing and Analysis—ISPA2005, pp. 353-358, 2005

[10] Attardi G, Betr M, et al. 3D facial reconstruction and visualization of ancient Egyptian mummies using spiral CT data Soft tissues reconstruction and textures application[A]. Los Angeles, CA: ACM SIGGRAPH Publications[C], 1999: 223 -239.

[11] Giuseppe Attardi, Marilina Betr, et al. 3D facial reconstruction and visualization of ancient Egyptian mummies using spiral CT data Soft tissues reconstruction and textures application.

[12] Kahler K, Haber J, Seidel H P. Reanimating the dead: Reconstruction of expressive faces from skull data[A]. Proceedings of SIGGRAPH'03 [C]. San Diego: ACM, 2003 22(3):554–561.

[13] Claes P, Vandermeulen D, et al. Craniofacial reconstruction using a combined statistical model of face shape and soft tissue depths: Methodology and validation[J]. Forensic Science International 159S 2006: 147-158.

[14] Sederberg T , Parry S. Free-form Deformation of Solid Geometric Models[C]. SIGGRAPH conference Proceedings, Dallas, USA, 1986, 20(4): 151-160 .

[15] Noh J Y, Fidaleo D, Neumann U. Animated deformation with radial basis functions. Proceeding of ACM Symposium on Virtual Reality and Software Technology. 2000: 166-174.

[16] Igarashi, T., Moscovich, T., Hughes, J.F. 2005. As-rigid-as-possible shape manipulation [C]. ACM Trans. Graph.24, 3, 1134-1141.

[17] Jin H, Xiaohan S, Xinguo L, Kun Z, et al. Subspace gradient domain mesh deformation. ACM Trans. Graph., 25(3):1126-1134, 2006.

[18] K. Sundaraj, Virtual deformation of soft tissue using bulk variables, WSEAS Transactions on Information Science and Applications, 2009, 6(10) : 1707-1718.

[19] Yuwen Lan, Yuewei Li, ShouRong Chen et al. The research on the indices of 3D Craniofacial reconstruction system [A]. The 11th Scientific Meeting of the International Association for Craniofacial Identification [C], dalian, 2004: 102-121.

[20] Jiarui Bao, Ronghua Liang, Fuli Wu, Xianping Huang et al. The Study On the Algorithm of Complex Hole Repairing on 3D craniofacial model. Journal of Image and Graphics, 2009.

[21] M. Rodrigues, A Robinson, L. Alboul, W. Brink, 3D Modelling and Recognition, In Proceedings of the 6th WSEAS International Conference on Signal Processing, Computational Geometry & Artificial Vision, Elounda, Greece, 2006: 72-76.

[22] ALEXA, M., COHEN-OR, D., AND LEVIN, D. 2000. As-rigid-as-possible shape interpolation. In Proceedings of ACM SIGGRAPH 2000, ACM Press/Addison-Wesley Publishing Co., New York, NY, USA, 157–164.

[23] Chenggang Li, Sanjeev Bedi, Stephen Mann. Flank Milling Surface Design with the Least Square Approach, WSEAS Trans Math 5(7): 844-852, July ISSN 1109-2769.

[24] Irina Semenova, Vladimir Savchenko, Ichiro Hagiwara. Curvature Based Mesh Improvement, WSEAS TRANSACTIONS on SYSTEMS, Issue 4, 2004, 3(4): 1346-1354.