Use of the dynamic volume spline method to predict facial soft tissue changes associated with orthognathic surgery

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Objective. The shape of the face can be estimated before the surgery by using 3-dimensional computer programs that provide tools to guide skill modifications. The aim of this study was to present the dynamic volume spline method to predict facial soft tissue changes after the modification of the skull associated with orthognathic surgery.
Study design. Soft tissue volume is modeled by a dynamic volume spline that includes the elastic behavior of the actual tissue. The model is a hybrid of spring-mass model and finite element model, and combines their advantageous properties. It provides fast and realistic soft tissue simulations. Postsurgical shape of the patient's face is estimated by reshaping the skull and letting the soft tissue model relax over the new boundary conditions formed by the new skull shape. Postsurgical estimations were compared with the conventional method's estimations, where the soft tissue is not modeled biomechanically. Also, postsurgical estimations were compared with the actual postsurgical data for 6 orthognathic surgery patients.
Results. The mean of the error between the estimated shapes and the actual postsurgical shapes was ~1.8 mm when the whole face was considered.
Conclusion. When the facial soft tissue is modeled by the dynamic volume spline, the postsurgical shape is estimated better than by the conventional method and previous methods in the literature. **(Oral Surg Oral Med Oral Pathol Oral Radiol Endod 2010;110:e17-e23)**

Planning before maxillomandibular surgery is important to increase the overall success of the operation by performing the modifications virtually before the actual operation. For patients seeking surgical treatment, it is very beneficial to have a means to predict the postsurgical appearance of their face. Depending on the type, significance, and outcomes of a surgery, this planning may differ. Currently, the planning procedure is mainly performed with the help of 2-dimensional (2D) images (photographs, lateral cephalograms) of the patients with the collaboration of surgeons and orthodontists. Needless to say, this procedure is highly dependent on user intervention or iuser confidence, because the 3-dimensional (3D) reality is investigated and planned only on 2D images. In recent years, the planning is done by using 3D computer-assisted surgery simulation (CASS) programs[1] which provide tools to modify the skull. These tools do not model soft tissue but cover the new shape of the skull with the original soft tissue thickness values extracted from the preoperation data. This type of planning will be refered to as the conventional method throughout this paper.

For prediction of soft tissue rearrangements produced by surgical interventions, a computational model of deformable objects is required. This model should react to the applied forces in a realistic fashion and in real time. Human soft tissue has nonhomogeneous, anisotropic, nonlinear, and viscoelastic behavior. So it is not possible to model the biomechanical complexity of the actual soft tissue. Instead, a simplified model is used to decrease the implementation complexity and to optimize computational efficiency. Once a virtual model of the patient is generated, various case scenarios of the surgical operation and its impact on soft tissue can be studied extensively. This provides the surgeon with unique feedback during the planning stage. The realism of surgical simulation depends on the ability of the deformable model in simulating the tissue mechanics.

The accuracy of computer models in predicting soft tissue response subsequent to skeletal changes after orthognathic surgery has been investigated in many studies. Only a few of them showed accurate prediction outcomes compared with the actual results.[2] The most significant area of error in prediction through the available computer prediction programs was in the lower lip area. A 3D CASS planning method was used for the treatment of patients with complex craniomaxillofacial

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deformities.[1] The dentofacial bone was cut and replaced and the soft tissue moved by radial basis functions.[3] Numeric simulation of soft tissue mechanics was performed using linear and nonlinear finite element model[4] (FEM). A linear FEM, a nonlinear FEM (NFEM), a linear mass spring model (MSM) and a linear mass tensor model were used as soft tissue simulators.[5] A modified MSM was proposed which was equivalent to a linear FEM.[6] The average errors of 8 soft tissue landmarks were measured to be between 0.37 and 2.01 mm, except 1 landmark that had an error of 4.44 mm. MSM values were found to be very close to those obtained with the linear FEM. A nonlinear finite mixed-element model was proposed based on solid-shell elements.[7] The model addressed the heterogeneity in geometry and material.

Thus, researchers have used both linear and nonlinear FEMs to develop soft tissue models. A computationally fast and stable simulation is possible by using a linear static FEM, although the linearity assumption is not valid for soft tissues with complex nonlinear behavior. NFEM models are more accurate but are computationally complex. Therefore, MSMs have been used extensively as a potential solution for real-time simulators. In a majority of these models, nonlinear spring coefficients, complex mesh structures, and volume preservation are implemented to increase the quality of the viscoelastic behavior of the soft tissue model. FEM has a very strong biomechanical relevance and is more accurate than other models. However, it has a high computational cost and large memory usage. MSM, on the other hand, has very easy architecture and low memory usage, but it is hard to control volume conservation during simulation, and accuracy is lower than with FEM.[5-8]

The trade-off between simulation accuracy and real-time computation still remains unresolved for soft tissue simulators. Hybrids of FEM and MSM are expected to perform better in both accuracy and efficiency. In the present study, a new hybrid model in the form of dynamic volume spline is proposed for facial soft tissue simulation. The dynamic volume spline is similar to Terzopoulous's dynamic nonuniform rational B-splines (NURBS) surfaces[9] in the sense that control points are localized masses with viscoelastic structural members attached to them. Differently from dynamic NURBS, volume physics is modeled instead of surface physics. The parameters of the present dynamic volume model (i.e., stiffness, damping, and mass) for human facial soft tissue were obtained from the literature. The model was used to simulate patients of maxillofacial surgery, and postoperation shapes were computed from preoperation shapes. The results were compared with the actual postoperative shapes.

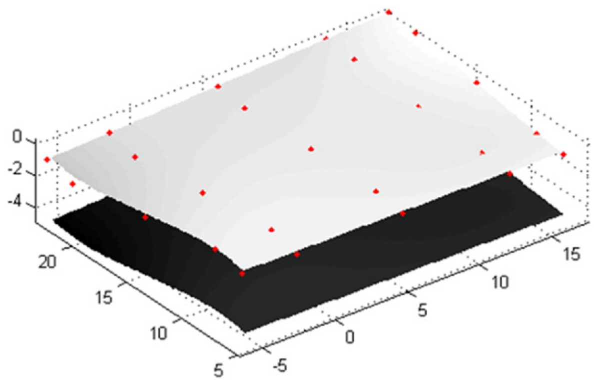

Fig. 1. A piece of skin material segmented from the forehead of the patient's computerized tomography data and the volume spline control points as red dots.

In the next section, dynamic volume spline is explained. In the subsequent section, application of the soft tissue model and postsurgery estimation results are shown for 6 patients. The results are compared with the conventional method where the soft tissue is not modeled and with the actual postsurgical 3D data of the patients. Finally, we provide concluding remarks and describe future work.

MATERIALS AND METHODS

A volume spline with M × N × P control points is fit to the soft tissue volume which is obtained by segmenting the computerized tomography (CT) data. The general volume spline equation is written as follows:

$$S(u, v, w, \mathbf{C}) = \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{p=1}^{P} (C_{m,n,p} \cdot N_{m,k}(u) \cdot N_{n,s}(v) \cdot N_{p,l}(w)) \quad (1)$$

Here $S(u,v,w,C)$ is the 3D position of a point inside the volume in general coordinates (u,v,w), $C_{m,n,p}$s are the 3D control points of the volume spline, and $N_{...}(.)$s are the basis functions.

In Fig. 1, a piece of human skin material of size 20 × 15 × 2 mm is shown. This piece is segmented from the forehead region of the patient's CT data. A volume spline with 5 × 5 × 2 control points is fitted to the surface. The spline control points are shown as red dots on the surface. The whole surface is modeled by 50 control points, and the whole surface can be reshaped by moving these control points.

The control points of the volume spline are considered as localized masses having localized stiffness and damping functions. The equation of motion for these control points can be rewritten as follows:

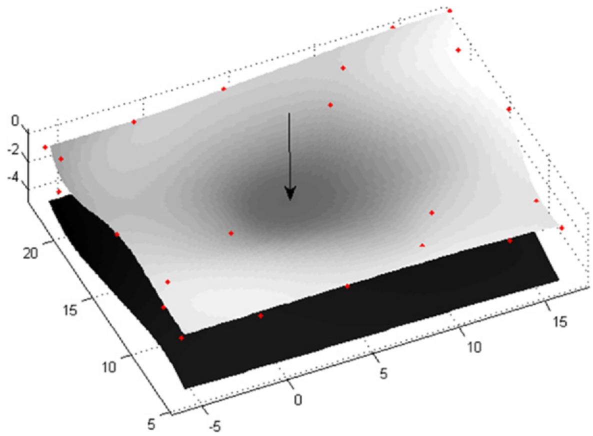

Fig. 2. A piece of skin material segmented from the patient's computerized tomography data and the volume spline control points as red dots when some force is applied on the skin surface.

$$M\ddot{C} + D\dot{C} + KC = F \quad (2)$$

Here M represents the localized mass for each control point and the covariant relation of mass distribution among the control points, K represents the localized elastic relations among the control points, D represents the localized damping coefficients of the control points and the covariant relation of energy loss among them, and F is the generalized force vector.

The differential equation (2) is solved through time. If the initial state is the resting state before the application of force, then the initial C will be the initial locations of the control points of the volume, and the initial $\dot{C}$ will be zero. Starting from this initial state, the positions of the control points through time can be computed when an external force is applied to the model or when some of the control points are given predefined displacements such as by simply moving them to new locations. When the model reaches the steady state eventually, the volume will have its final shape. The new surface model can be obtained from the new positions of the control points by equation (1).

In Fig. 2, the same skin model is shown when some force is applied on the skin surface. The new positions of the control points are given as red dots. When a force (in the direction shown by the arrow) is applied to the surface, the surface should bend toward the inside. In the dynamic volume spline model, the effect of the force on the surface points are not considered, but the force is distributed among the control points (C) and they move based on equation (2) and thus the surface shape changes accordingly. Thus, instead of controlling all of the surface points one by one, only the control points are affected, and the whole surface takes a new shape based on the control points.

The effect of a change in the boundary condition of the skin model has the same effect as the effect of force application on the skin surface. If the hard surface under the skin (i.e., the skull) shape changes, then this makes the control points change and in the end this makes the skin model change and take the new shape of the new boundary. In the present study, the soft tissue takes its new shape based on the elasticity considered in the volume spline model. With the orthognathic surgery, the shape of the skull changes so that the boundary conditions change, causing the skin model to take a new shape consistent with the actual tissue behavior.

RESULTS

In the present paper, we propose a planning procedure which is based on 3D anatomic and biomechanical information of both hard and soft tissue. The anatomic data is obtained from the preoperation CT data by segmentation. The hard tissue is modeled as rigid. The soft tissue is modeled by dynamic volume spline which sits over the hard tissue. The model requires 3 parameters: stiffness, damping, and mass density. Values of these parameters were obtained from the literature. In the literature, stiffness and damping values for forearm, thigh, and scalp skin range between 12 and 750 N/m and between 0.08 and 350 Ns/m, respectively.[10-16] The mass density for skin is given as 1,100 kg/m^3.[12] In the present study, 1,100 kg/m^3 was used as mass density, 80 N/m for stiffness, and 1 Ns/m for damping.

The planning was done for 6 patients using their preoperation data. The skull was cut and moved according to the requirements of the surgery. Then the skin model was let to relax over the new skull shape, i.e., the new boundary conditions. The results were compared with the actual postoperation data. In this section: first, we provide information about the patients and the operations; second, we explain the conventional planning (without using soft tissue model); third, we summarize and visualize our proposed planning (with biomechanical modeling of soft tissue); and finally, we compare results with and without the soft tissue model and the actual postsurgical data.

Patients and operation details

Surgery planning typically starts with the general diagnosis of a patient. Six patients (mean age 24 $\pm$ 6.1 years, 2 female, 5 male) having orthognathic surgery participated in this study. The patients with class III malocclusion and concave facial profile were scheduled for bimaxillary orthognathic surgery. The patients with other malocclusions underwent maxillary advancement (Le Fort I) and mandibular setback (bilateral sagittal

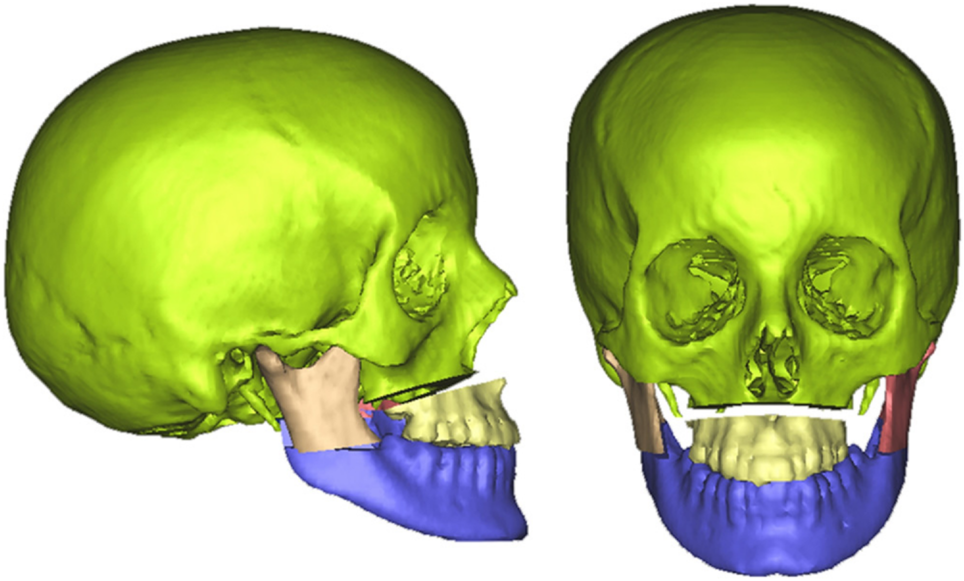

Fig. 3. Three-dimensional virtual operation on a patient's skull.

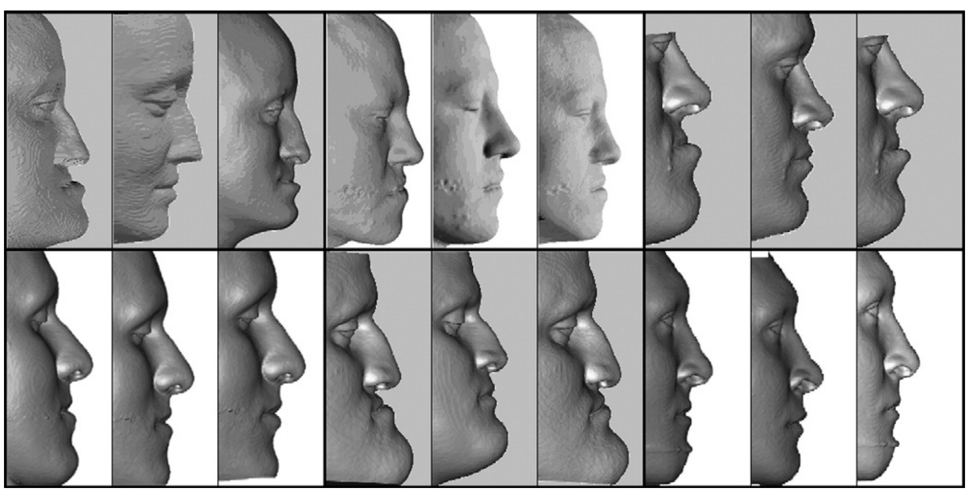

Fig. 4. Presurgical face computerized tomography model (left), postsurgical face model (middle), and three-dimensional virtual simulation result of the conventional method (right) for 6 different patients.

split osteotomies). All patients had undergone presurgical-postsurgical orthodontics, and CT and magnetic resonance data and lateral cephalograms were taken after the completion of treatment.

Conventional planning

The part of the skull is cut and repositioned, or some gaps are filled on the skull so that the initial skull can be reshaped. In Fig. 3, the maxilla and the mandible which are cut and dislocated according to the surgery plan for a patient using MIMICS[17] are shown. Soft tissue biomechanics is not modeled, and the soft tissue volume is covered (warped) over the bone structure directly. The same skin thickness in the presurgical model is covered over the postsurgical skull shape. In Fig. 4, the data of 6 patients with different degrees of esthetic problems are shown. The presurgical and postsurgical CT models of the patients and the results of the virtual plan obtained based on the presurgical CT models by the conventional method are given in the figure as triplets.

Realistic soft tissue modeling

First of all, dislocation and rotation of maxilla and mandible are applied to the 3D skull model according to the surgery planning parameters similarly to the con-

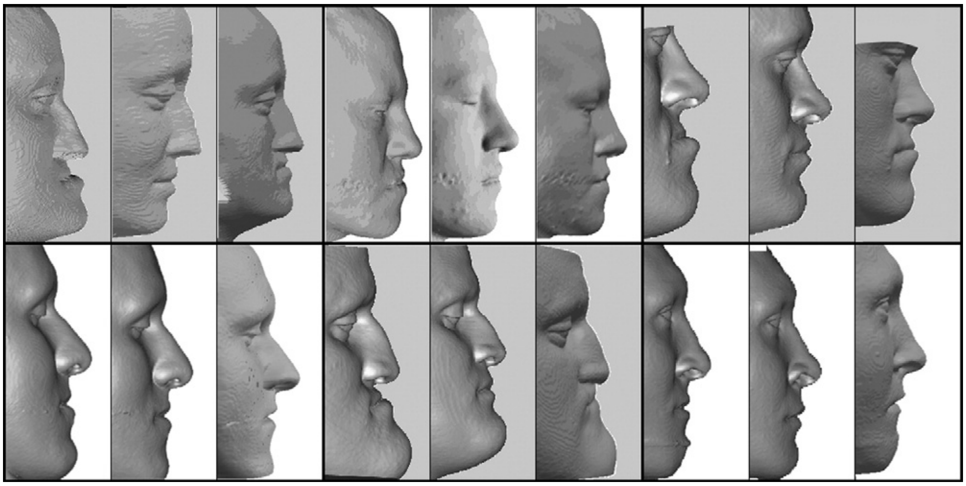

Fig. 5. Presurgical face computerized tomography model (left), post-surgical face model (middle), and three-dimensional virtual simulation result of our method (right) for 6 different patients.

ventional method. This step is the same in both methods. But differently from the conventional method, the soft tissue is modeled by the biomechanical model, i.e., the volume spline model. After the skull is properly operated, the reshaping of the skull causes a change on the boundary conditions for the dynamic skin model. This change is a disturbance for the model and when the model is solved based on equation (2), the model relaxes and takes its new shape over the new skull shape. Owing to the elastic behavior of the skin model, the model deforms over the new skull shape. Finally, the new shape of the face, i.e., the postsurgery estimation is obtained.

In Fig. 5, the presurgical and the postsurgical CT models of the same patients given in Fig. 4 and the results of the virtual plan obtained based on the presurgical CT models by using the soft tissue model are given. For all patients, the estimation is closer to the actual postsurgery shape than the estimation of the conventional method.

Comparison

To visualize the similarities and differences between our postsurgery estimation and the conventional postsurgery estimation, a number of analysis are performed. The differences are computed between current estimation and the actual postsurgical model and between conventional estimation and the actual postsurgical model. For this purpose, the models to be compared are registered by using the iterated closest points method[18] provided by the Meshlab tool.[19,20] Then differences between the models are computed by the Metro tool,[21,22] where a surface is sampled uniformly and differences between these sampled points and the closest points in the other model are computed.

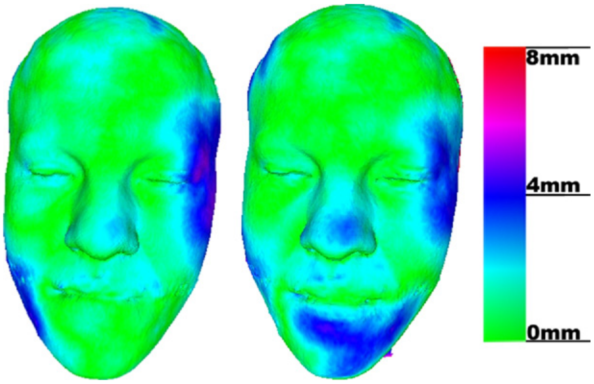

Fig. 6. **A,** The difference image between the actual postsurgical result and our estimated model (left) and the difference image between the actual postsurgical result and the estimated model using the conventional method (right).

In Fig. 6, the difference image between the actual postsurgical result and the estimated model using the current model and the difference image between the actual postsurgical result and the estimated model using the conventional method are depicted for a patient. Each color represents a difference value in millimeters as indicated in the color scale. The difference is high for the chin area, especially for the lower lip area, as stated in the literature.[2] Also, the difference is bigger for complex operations, as can be expected. The difference between the actual postsurgical shape and the estimated postsurgical shape is more when the conventional method is used.

In Table I, the mean values of the differences are listed for all of the patients. The difference for the conventional method is higher than for our method. The

Table I. Means of differences, mm

Patient	*Between actual postsurgical CT and current estimation*	*Between actual postsurgical CT and conventional method estimation*
1	1.1	3.1
2	1.3	3.1
3	1.2	1.4
4	1.3	1.3
5	4.6	4.9
6	1.3	1.1

CT, Computerized tomography.

mean of error for the conventional method (2.48 mm) is nearly 1.5 times more than the mean of error for our method (1.8 mm). Also, the error mean for our method is less than many other methods in the literature.[2]

Because patients usually lose weight during the treatments, the soft tissue volume of the face changes.[23] Therefore, the estimated model based on the presurgical data can never be the same as the actual postsurgical data.

DISCUSSION

Previously, soft tissue modeling has been done by FEM, MSM, and their different versions.[5-8] In the present study, an anatomic and dynamic volume spline model is proposed for human facial soft tissue modeling. This is a hybrid model that has the properties of both FEM and MSM. The model is based on the spline formulation of control points which are localized masses with viscoelastic material properties. Thus, instead of the original data points that may be many in number, the model is governed by the control points that are fewer than the data points. For this reason, the computational advantage of this model lies within its ability to lower the number of dynamically calculated points by using splines. The model is a volume model as opposed to many existing spring mesh and dynamic spline surface models. Thus, volumetric physics is applied instead of surface physics.

Furthermore, the model was tested for 6 facial surgery planning simulations. For this purpose, the surgery plans required for the operations were analyzed and the planned operations simulated in 3D biomechanical face models. The postsurgery estimations were compared with the actual postsurgical facial shapes of the patient. The same surgery planning was also done by the conventional method, and the postsurgery estimation of the conventional method was also compared with the actual postsurgery data. Our estimations were always closer than the conventional method's estimations to the actual postsurgical shape. The conventional method does not model soft tissue biomechanically, using only the geometric model. Because we model the skin by the dynamic volume spline, which includes the viscoelastic behavior, our model estimates postsurgical shape better. During surgery and postsurgical treatment, patients usually lose weight, so we can never expect zero difference.

In an earlier study, pre- and postsurgical shapes of the nose were obtained by a 3D scanner and the shapes compared based on some points on the nose.[24] Similarly, instead of CT or magnetic resonance data, we can scan the face of the patient after surgery and perform comparisons using this data. This type of skin modeling may also be used for other orthognathic surgery applications.[25]

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