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Prediction of soft tissue deformations after CMF surgery with incremental kernel ridge regression

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ABSTRACT

Facial soft tissue deformation following osteotomy is associated with the corresponding biomechanical characteristics of bone and soft tissues. However, none of the methods devised to predict soft tissue deformation after osteotomy incorporates population-based statistical data. The aim of this study is to establish a statistical model to describe the relationship between biomechanical characteristics and soft tissue deformation after osteotomy. We proposed an incremental kernel ridge regression (IKRR) model to accomplish this goal. The input of the model is the biomechanical information computed by the Finite Element Method (FEM). The output is the soft tissue deformation generated from the paired pre-operative and post-operative 3D images. The model is adjusted incrementally with each new patient's biomechanical information. Therefore, the IKRR model enables us to predict potential soft tissue deformations for new patient by using both biomechanical and statistical information. The integration of these two types of data is critically important for accurate simulations of soft-tissue changes after surgery. The proposed method was evaluated by leave-one-out cross-validation using data from 11 patients. The average prediction error of our model (0.9103 mm) was lower than some state-of-the-art algorithms. This model is promising as a reliable way to prevent the risk of facial distortion after craniomaxillofacial surgery.

1. Introduction

Human facial appearance plays an important role in individuals' quality of life. In many patients with craniomaxillofacial (CMF) deformities, both bones and facial soft tissues are involved, and patients undergo surgery to rectify such deformities. The success of CMF surgery depends not only on the technical aspects of the operation, but also on a precise presurgical plan [1–4]. Currently, surgeons can accurately plan osteotomies (surgical procedures on bone), but cannot accurately predict soft-tissue deformation after osteotomy despite multiple attempts at presurgical planning.

Facial soft tissue deformation following osteotomy is associated with biomechanical characteristics of bone and soft tissues [5,6]. Currently, there are three main methods to simulate soft-tissue deformation utilizing biomechanics. The first is the mass spring modeling (MSM) method [7,8]. This model represents the face as a collection of assembled mass-spring entities. This model has an easy architecture, which benefits computational speed. However, it is less biomechanically relevant because it does not incorporate the biomechanical characteristics [9]. The second is the finite element modeling (FEM) method [10–12]. This method is based on biomechanics to characterize the relationship between tissue deformations and biomechanical properties, and thus is more biomechanically relevant. FEM can be categorized into two classes: linear and nonlinear [13]. Linear FEM results from linear elasticity with isotropic, linear, and elastic material. When the materials are modeled as non-isotropic or non-elastic, a nonlinear FEM result occurs. The difference in the prediction of soft-tissue deformation between linear and nonlinear FEM is controversial. One study reported only that there was a difference between prediction results using linear and nonlinear FEM [13], while another reported that linear FEM outperformed the nonlinear FEM method [9]. However, FEM has the disadvantage of being computationally costly. The third method is the mass tensor modeling (MTM) method [14,15],

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which is a mixture of the FEM and MSM approaches. It has the easy architecture of MSM, and at the same time keeps the biomechanical relevance of FEM. MTM can achieve accuracies comparable to those of linear FEM, while reducing the computational cost [9].

Unfortunately, none of the above methods includes population-based statistical information. Since we can collect patients' preoperative and postoperative 3D images, it should be possible to establish a statistical model to yield statistical dependencies from the individualized soft tissue deformations. Meller et al. proposed the statistical deformable model (SDM) to capture the variety of preoperative facial morphologies in a group of patients, and their compared their corresponding postoperative deformations from 3D surface scans [16]. After fitting preoperative data for a new patient into the model, the postoperative morphology could be extracted. One drawback of this method was that it did address this need, we reported a preliminary two-step algorithm, in which FEM was first performed to extract the nodal displacement features, and SDM was then used to learn the statistics of the nodal displacement over patients' preoperative data [17]. However, this approach was an unsupervised method, in which real postoperative data were not used. This could be a source of inaccuracy.

There are different types of CMF deformities, and even within the same deformity (i.e. Angle's Class III), many variations exist. An ideal set of training data would include every deformity and its variations to simulate soft tissue change. However, none of the currently available training data sets includes such variations. To remedy this limitation, deformities of new patients should be included into the statistical model. We conjecture that new patients' biomechanical properties will help make prediction of postoperative soft tissue changes more accurate.

The goal of this paper is to establish a statistical model to describe the relationship between biomechanical characteristics and soft tissue deformations. We develop an incremental version of the kernel ridge regression (KRR) model, which not only builds nonlinear relations between biomechanical information and soft tissue deformations, but also is incrementally adjusted by incorporating the new patients' biomechanical characteristics. The proposed model, called the incremental kernel ridge regression (IKRR) model, first trains a KRR model from a set of paired preoperative and postoperative 3D data, then adds biomechanical data from new patients into the KRR model. Prediction of IKRR is the convex combination[2] of the predictions of KRR and FEM, where the combination coefficients are controlled by the trade-off parameter of KRR. Compared to [12], our model makes use of new patients' information, and more importantly, also utilizes the supervised information (postoperative 3D data). The proposed method was validated in 11 patients. The IKRR model achieved lower prediction errors than other evaluated methods, which are Linear Finite Element Modeling (LFEM) [9], Statistical Deformable Model (SDM) [17], and Ridge Regression (RR). And it produced more faithful visualizations of the predicted images. Furthermore, the IKRR model was experimentally more efficient than the KRR model, and updated the model with new data.

The notations used in the paper were described. Vectors were denoted by bold lower case letters, and matrices by upper case ones. Vectors are denoted by bold lower-case letters, and matrices by upper-case ones. The transposes of a vector $\mathbf{a}$ and a matrix $\mathbf{A}$ are represented by $\mathbf{a}^T$ and $\mathbf{A}^T$, respectively. The inverse and the determinant of a square matrix $\mathbf{A}$ are denoted by $\mathbf{A}^{-1}$ and det $\mathbf{A}$, respectively. We use $\mathbf{I}_n$ to denote the n by n identity matrix. The Euclidean norm of a vector $\mathbf{a}$ is denoted by $\|\mathbf{a}\| = \sqrt{\mathbf{a}^T\mathbf{a}}$.

[2] A *convex combination* is a *linear combination* of *points* where all *coefficients* are *non-negative* and sum up to 1.

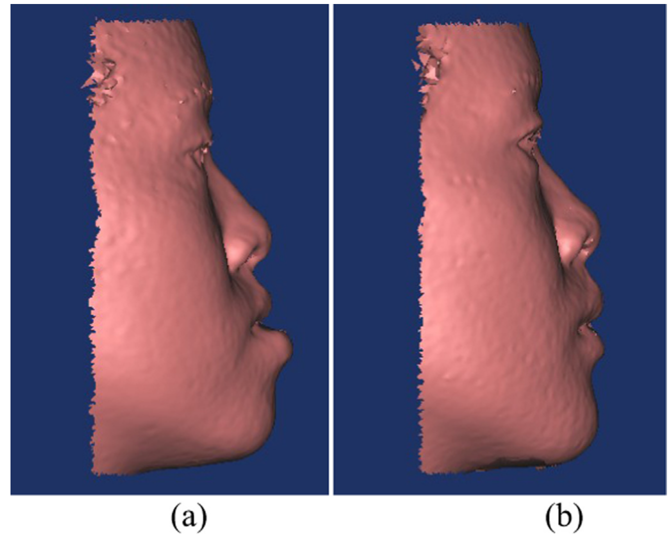

Fig. 1. (a) The preoperative surface scan and (b) the postoperative surface scan.

This paper completes our conference paper [18] by including more details of our methods and additional experiments.

2. Materials and methods

Fig. 1 shows the preoperative and postoperative surface scans of a patient. To improve his facial appearance and to reduce the prominence of his chin, this patient underwent surgery to set back the mandible (bilateral sagittal split osteotomies) and advance the maxilla (Le Fort I osteotomy). We left the osteosynthesis material. The postoperative surface scan was acquired 6 months after surgery to avoid surgical swelling.

The FEM method was used to extract biomechanical information from the CT images. Then a regression model was used to establish the statistical relationships. As a new patient's data arrived, the learned regression model was employed to predict the resulting soft tissue changes. The whole procedure was divided into two phases. In the first phase, named the training phase, we established regression models. The second phase, named the test phase, involved predictions of soft tissue deformations of new patients. Fig. 2 presents a flowchart of the two phases.

In the training phase, we collected a set of preoperative and postoperative 3D images. The features were extracted from the preoperative images with FEM. The details of feature extraction are shown in Fig. 3. First, a detailed anatomic template was generated to be applicable to all data. The template helped to automatically generate the anatomic detailed mesh for each patient, which substantially reduced the workload. The displacement boundary condition (surgical plan) could be determined from the paired preoperative and postoperative skulls. After obtaining the mesh and displacement boundary conditions, we employed FEM to extract biomechanical information of individuals. The extracted features were then imported as the input in the regression model. The output in the regression model represented the true displacements of the corresponding nodes in the preoperative and postoperative meshes. As data from a new patient became available, we adjusted the model to incorporate his/her biomechanical information. The displacements of mesh nodes of the new patient were predicted from the adjusted model. Predictions of postoperative appearance were visualized by using interpolation techniques.