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Large Deformation Estimation between Prone and Supine Breast Meshed Models

Xiaoyu Song, Zhaobin Kuang, Kang Zheng, Mengke Lian, Fang Qi

Abstract—**Preoperative magnetic resonance (MR) breast images provide anatomical information about the lesion. By registering preoperative images to images in surgery, physicians can perform tumor excision more precisely. Preoperative imaging is performed in the prone position while breast surgery is in the supine position. Since breast is very deformable, large deformation is introduced, and its estimation has been a major challenge. We present a novel method to address this challenge and demonstrate its application in the deformation estimation between prone and supine breast meshed models. Firstly, we construct prone and supine meshed models via MR images and finite element method (FEM). Secondly, a revised surface registration scheme based on spherical harmonic analysis is employed to compute the displacement field on the surface. Finally, we expand the displacement field to internal by mean value interpolation. Our method takes advantage of the inherent anatomical feature and deformation of breast models. Compared with FEM, a prevailing solution for large deformation estimation, our method is easy to implement, irrelevant to biomechanical analysis and requires minimal segmentation. Experimental results show our method is a good approximation for FEM.**

I. Introduction

Preoperative magnetic resonance (MR) imaging (e.g. dynamic contrast enhanced imaging) provides anatomical information about the tumor in the breast. By registering preoperative images to images in the surgical position, physicians are more informed about the size and location of the lesion, consequently increasing the accuracy of tumor excision. Preoperative breast MR imaging is performed in the prone position while breast surgery is performed in the supine position. Since breast is a very deformable organ in the human body, large deformation is involved and its estimation is a challenging requirement during registration [1]. Based on finite element method (FEM), patient specific biomechanical breast model has become a prevailing method to estimate large deformation between the two positions [1]-[6]. High accuracy breast surgeries with the assistance of FEM have also been reported [4]. Although these applications indicate a tempting solution for large deformation estimation, there are several concerns about FEM: 1. The modeling process of FEM is usually complicated and assumptions have to be made about material properties of breast tissues, constraint and loading condition to perform biomechanical analysis. Incorrect assumptions might lead to the failure of modeling process [2]; 2. The implementation requires segmentation of different breast tissues and misclassification might affect the accuracy of the model [5]; 3. Biomechanical models based on FEM are usually difficult to verify and evaluate [6].

In this paper, we propose a novel method for large deformation estimation. By combining spherical harmonic (SPHARM) analysis based surface registration algorithm [7] with mean value coordinates (MVC) [8] interpolation technique, we compute the displacement field from prone breast meshed model to its supine counterpart and achieve registration between the two models. For implementation convenience and efficiency, our method takes advantage of the inherent anatomical feature and deformation of breast models. Prone and supine meshed models are constructed based on MR images and FEM. SPHARM based surface registration algorithm provides point-to-point correspondence between the two breast model surfaces. Based on the correspondence, displacement field on the breast surface can be computed easily. MVC interpolation technique is applied to expand point-to-point correspondence to the internal volume of the breast model by linearly interpolating the displacement field on the surface to internal. Compared with FEM, the advantages of our method are threefold: 1. Our method is based only on the geometric information represented by the two breast models. Therefore, classification of different breast tissues, modeling of breast tissue material properties, constraint or loading condition is not required; 2. Since there is no need to classify different breast tissues and assign material properties, minimal segmentation is required only to separate the whole breast volume from other parts of the human body; 3. Our method is easy to verify and evaluate whether it is a good approximation for FEM, as the supine model is constructed by FEM based on its prone counterpart.

II. Method

We present our large deformation estimation method and demonstrate its application in the deformation estimation between prone and supine breast meshed models. Figure 1 shows the procedure for estimating large deformation between prone and supine using the developed method.

The estimation process consists of four major steps as follow:

Step 1: Model construction. Prone breast meshed model is generated from MR images by segmentation technique. Supine model is constructed by deforming the prone model using FEM.

Step 2: Surface registration. We first establish point-to-point correspondence between the two model surfaces. Here, we use an anatomical-feature-guided SPHARM registration algorithm derived from **SPH**ARM **RE**gistration with I**C**P (SHREC) [7]. Then we take the

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Xiaoyu Song, Zhaobin Kuang, Kang Zheng, Mengke Lian and Fang Qi are with Laboratory of Physical Diagnosis, Bio-X Center, Harbin Institute of Technology, Harbin, Heilongjiang, 150080 China. (email: songxyhit @hit.edu.cn)

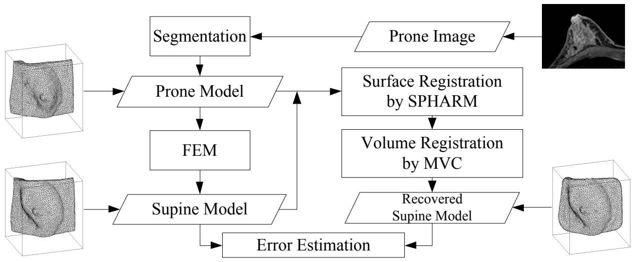


Figure 1. Diagram of the proposed large deformation estimation procedure

difference between the coordinates of each corresponding pair to compute the deformation field.

Step 3: Volume registration. We use the inherent deformation between prone and supine surfaces as boundary condition for MVC [8]. Then we linearly interpolate the displacement field on the breast surface to its internal volume. Internal displacement field will be represented as a weighted sum of displacement at each point on the surface.

Step 4: Error Estimation. Step 2 and step 3 will generate the displacement field on the whole breast volume. Then we compare the displacement field with that generated by FEM to verify the accuracy of the proposed method.

A. Model Construction

To generate a prone meshed model, we use ITK-Snap (http://www.itksnap.org/) [9] for segmentation (a set of prone breast images is separated from human body), and for automatic construction. Then we discretize the shape with four-node tetrahedral elements. Biomechanical analysis based on FEM [3] is applied to deform the prone model to its supine counterpart in ABAQUS [10], a commercial FEM software package. Note that we can also acquire a supine mesh model by segmenting supine MRI breast images [4]. However, we prefer to acquire the model through biomechanical analysis. The reasons are twofold: 1. Biomechanical literature suggests that FEM is a decent approximation for large deformation [1]-[6]. 2. Prone and supine FEM models provide inherent vertex-to-vertex correspondence between each other, and will serve as a good benchmark for comparison.

B. Surface Registration

The goal of surface registration is to compute the displacement field between the two model surfaces, by establishing point-to-point correspondence between each other. Surface registration algorithm employed here is based on SPHARM analysis. The process consists of four steps: 1. Spherical parameterization; 2. SPHARM expansion; 3. Surface registration; 4. Displacement field computation.

1) Spherical parameterization

As SPHARM functions are defined on the unit sphere, spherical parameterization provides the domain for SPHARM analysis in the following steps. Given a breast meshed surface model M, which is a closed genus zero surface, its topological domain is a unit sphere S^2. M is defined on the Cartesian coordinates system, denoted as (x, y, z). S^2 is defined on the unit spherical coordinates system, denoted as (θ, ϕ), where $\theta \in [0, \pi]$ is the polar component, and $\phi \in [0, 2\pi]$ is the azimuthal component. We compute a bijective map $\vec{f} : M \to S^2$ using a spherical mapping algorithm [11]. It generates a spherical parameterization:

$$v(\theta, \phi) = (x(\theta, \phi), y(\theta, \phi), z(\theta, \phi))^T \tag{1}$$

where v is a vertex on M. The mapping is conformal so as to preserve local geometric information. $\vec{f}$ is initialized as a homeomorphism by centroid projection:

$$\vec{f}(v) = \frac{v - c}{\|v - c\|} \tag{2}$$

where c is the centroid of the model. Then the initial homeomorphism is optimized to acquire the resultant map by minimizing the discrete harmonic energy iteratively. The discrete harmonic energy is defined as:

$$E(f) = \sum_{\{u,v\} \in M} k_{uv} \|f(u) - f(v)\|^2 \tag{3}$$

where $\{u, v\}$ is an edge on the mesh formed by vertex u and v, k_{uv} is a coefficient defined by cotangent scheme [12]. Steepest descent algorithm is employed for minimization [11].

2) SPHARM expansion

The goal of SPHARM expansion is to represent spherical parameterized surface in the frequency domain by SPHARM coefficients. Y_l^m is a SPHARM function of degree l and order m. SPHARM functions are a set of eigenfunctions of Laplace operator, which form an orthogonal basis in Hilbert space. After parameterization, closed genus zero surface can be represented as a linear combination of SPHARM basis:

$$v(\theta, \phi) = \sum_{l=0}^{L_{max}} \sum_{m=-l}^{l} c_l^m Y_l^m(\theta, \phi) \tag{4}$$

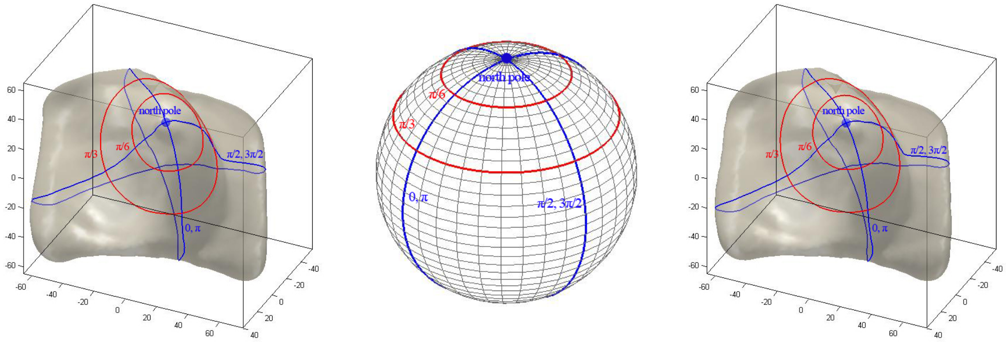
where $c_l^m = (c_{xl}^m, c_{yl}^m, c_{zl}^m)^T$ are SPHARM coefficients and bandwidth L_{max} is user-desired. In practice, in order to compute the coefficients, we first regularly sample the mesh. Then we employ fast spherical harmonic transform (FST) algorithm [13] to compute the coefficients in a divide and conquer strategy. We represent both prone and supine breast surface models using SPHARM expansion. The prone model is considered as a reference and the supine model is for registration. We denote the sets of SPHARM coefficients as $c_{l,ref}^m$ and $c_{l,reg}^m$, representing the prone and supine model respectively.

3) Surface registration

To describe the quality of alignment during surface registration, a cost function is constructed using SPHARM coefficient. Spherical parameterization provides natural point-to-point correspondence between manifolds: we define two points on the prone and supine models sharing the same coordinate (θ, ϕ) in the spherical parametric space as a corresponding pair. To optimize the correspondence, a widely used cost function is root mean square distance (RMSD) between the two surface models [7]. Using SPHARM coefficients acquired from expansion, RMSD is defined as:

$$\text{RMSD} = \sqrt{\frac{1}{4\pi} \sum_{l=0}^{L_{max}} \sum_{m=-l}^{l} \left\| c_{l,reg}^m - c_{l,ref}^m \right\|^2} \tag{5}$$

Then we achieve the optimization by minimizing RMSD. Using anatomical feature like nipple as landmark, we have revised an optimization scheme based on SHREC [7]. The idea behind the scheme is straightforward: We fix the reference breast model in parameter space and rotate the



(a) prone (mm) (b) spherical parametric space (c) supine (mm)

Figure 2. Surface registration between prone and supine breast models

parameterization of the registered model so as to find a new parameterization that minimizes RMSD. Then the problem summarizes to: 1. Computation of a rotated parameterization; 2. Find the optimized rotation.

we define a rotated parameterization as $c_l^m(\alpha,\beta,\gamma)$, where c_l^m is the original parameterization, (α,β,γ) is the Euler angle to rotate c_l^m in order to formulate the new one. Then we have:

$$c_l^m(\alpha,\beta,\gamma) = \sum_{n=-l}^{l} D_{mn}^l(\alpha,\beta,\gamma) c_l^n \tag{6}$$

where D_{mn}^l is the rotation matrix [7].

To determine the optimized rotation, we use the nipple as a landmark. We first rotate both reference and registered parameterization so as to align their north poles $(0,0)$ with the nipple. So the parameterizations are roughly registered. Then we fix the reference parameterization and rotate the registered one around the axis that passes through the north pole (nipple) until we acquire the minimal RMSD.

4) *Displacement field on the breast surface*

We have optimized point-to-point correspondence by surface registration. We denote the two vertices in a corresponding pair as v_{ref} on the reference (prone) model and v_{reg} on the registered (supine) model. Then the displacement field on the breast surface from reference to registered can be defined as:

$$d_{surf} = v_{reg} - v_{ref} \tag{7}$$

C. *Volume registration*

We use the inherent deformation between prone and supine surfaces as boundary condition, and linearly interpolate interior points without manual intervention. Similar to (7), we define the displacement field between the two internal breast volumes as:

$$d_{int} = v_{reg} - v_{ref} \tag{8}$$

where v_{reg} and v_{ref} are a corresponding pair of vertices in the internal breast volume. Then we can consider the displacement field of the whole breast volume as a function defined on the reference model:

$$d(v_{ref}) = v_{reg} - v_{ref} \tag{9}$$

To compute an estimation of d_{int}, we employ MVC interpolation as volume registration algorithm. MVC has favorable properties like interpolation, smoothness and linear precision [8]. It expands the displacement field on the surface to the internal volume, and hence establishes internal point-to-point correspondence. The process consists of two steps: 1. Weights computation; 2.Volume registration.

MVC can represent d_{int} at each internal vertex as a weighted sum of d_{surf} at all the vertices on the surface. Therefore, in order to represent d_{int} at one internal vertex, we should assign a weight to d_{surf} at every surface vertex. The weight is denoted as w_i, where i represents the ith vertex on the breast surface. w_i can be computed according to [8]. Then d_{int} can be computed by a weighted average formula [8]:

$$d_{int}(v) = \frac{\sum_i w_i d_{surf(v)}}{\sum_i w_i} \tag{10}$$

For detailed implementation, please refer to [8].

III. RESULTS

We used the proposed method to estimate the large deformation between prone and supine 3D breast meshed models. Then we compared the performance of the proposed method with that of FEM.

We performed MR imaging on 10 patients at prone position. The MR images of the breast were acquired using a SIEMENS Verio 3T scanner with 32×32 cm field of view, 320×320 resolution and 1.2-mm slice increment. The experiments were conducted with MATLAB 7.10.0, Intel® Core™2 Duo 2GHz CPU, 2GB RAM and Windows Vista Home Basic SP2. After segmentation, the whole registration process lasted about 350s, with a model reconstruction bandwidth of 40. Time cost varied slightly from model details such as the number of elements. The FEM models applied in our experiment were with Hookean elastic material properties [3]. We fixed the chest wall as boundary and employed gravity loading on the model. It took about 20s to compute the deformation after modeling. Note that a more accurate FEM model in practice usually takes minutes or even hours to implement, depending on the anatomical complexity as well as the modeling complexity of materials. Therefore, the proposed method is an efficient alternative for large deformation prediction.

Figure 2 (a) and (c) show the result of surface registration between prone and supine breast models. The bandwidth (l) of model reconstruction is 40. The blue point located on the nipple is the north pole. The two red closed curves on the model represent latitude $\theta = \pi/6$ and $\theta = \pi/3$ in the

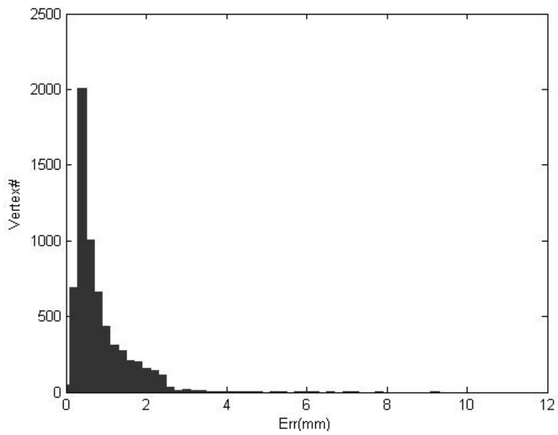


Figure 3. Error distribution of the internal volume compared with FEM

spherical parametric space respectively. The two blue closed curves represent longitude $\phi = 0, \pi$ and $\phi = \pi/2, 3\pi/2$. (b) shows the feature point and curves in the spherical parametric space. Visually, all the curves are well aligned between the two positions, indicating the two model surfaces are precisely registered. Therefore, the displacement field on the surface can be computed accurately.

Accuracy of surface registration is crucial to the determination of displacement field in the internal volume. This is because the internal displacement field is estimated as a weighted sum of displacement on the surface.

Figure 3 shows the error distribution of the recovered breast internal volume using the proposed method, compared with the FEM benchmark. Intuitively, most of the vertices have deformation error less than 3 mm. The average error is 0.83 mm, while the max error is 9.24 mm. During breast tumor excision, clinicians usually excise an extra margin of 10mm healthy tissues around the estimated extent of the lesion [4]. Therefore, this is a promising result. It demonstrates that the proposed method can recover the deformation field accurately and is a good approximation for FEM.

IV. DISCUSSION

In this paper, we have proposed a novel method to estimate large deformation from prone position breast meshed model to its supine counterpart. We employ SPHARM based surface registration algorithm to estimate the displacement field of deformation on breast surface. Then we expand the displacement field to its internal volume using MVC based linear interpolation technique. Both surface and volume registration between prone and supine breast models are achieved. We compare the performance of our estimation method with FEM. Experimental results show only small errors are introduced using our method. Therefore, it is a good approximation for FEM. Our method is only determined on the geometric information represented by the meshed models. It also avoids complicated biomechanical modeling process and involves minimal segmentation.

As suggested in section III, the accuracy of surface registration influences volume registration significantly. To improve the accuracy of surface registration, we will use a SPHARM registration method based on multi-landmark and spherical thin plate spline [14]. Then more feature points on the breast surface can be better aligned and hence should lead to a more accurate result.

Since MVC is a linear interpolation technique, it can provide volume registration results with linear precision. Therefore, the estimation is not good enough in some cases. To further refine our estimation results and make a step forward to clinical application, we will compute a set of simulated supine MR images using the prone images and the estimated displacement field. Then we will apply non-rigid image registration technique [6] to further register the simulated images with MR supine images acquired from experiments [4]. After non-rigid registration, large deformation should be more precisely predicted.

The presented method provides a general framework for large deformation estimation and can be applied for other surgical applications (e.g. brain, liver, lung) and multi-modality registrations (e.g. 3D ultrasound-MR, X-Ray-MR), where large deformations are also expected.

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