Fast Deformation Simulation of Breasts Using GPU-Based Dynamic Explicit Finite Element Method

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Abstract. In this study, we investigated the applicability of a Graphics Processing Unit (GPU)-based dynamic explicit finite element (FE) program for fast quasi-static deformation simulations of breasts, and proposed an optimisation-based method to estimate material parameters of *in vivo* breast tissues in the context of nonlinear hyperelastic models. Due to its high-speed execution, the GPU-based FE program was used as a forward solver in the optimisation process. A hybrid simulated annealing algorithm for global optimisation was employed to find the optimised material parameters by mininising the Euclidean distance between FE predicted displacements and estimated displacement from image registration at the selected landmark positions. The proposed method can be used for fast FE analyses of soft tissue deformations in medical image analyses and surgical simulations.

Keywords: Soft Tissue Deformation, Finite Element Method, Image Registration.

1 Introduction

Biomechanical models using finite element methods (FEMs) have been used to predict breast deformations in surgical simulations and in medical image analyses for assisting breast cancer diagnosis [1], [2], [3]. Typically the breast deformation during mammography [1], [3] is considered as a quasi-static problem and has been analysed using static implicit finite element methods (e.g. ANSYS [4]). In static implicit FEMs, the implicit integration scheme is employed to solve finite element equations using iterative methods (e.g. the Newton-Raphson method). Although the static implicit integration method is unconditionally stable and a bigger increment time step can be taken in the solution, it can encounter numerical difficulties converging to a correct solution during an analysis involving large deformations, highly non-linear material behaviour or contact, requiring a large number of iterations. Dynamic explicit FEMs, extensively applied to solve dynamic problems, have proved valuable in solving quasi-static problems when inertial effects can be neglected [5]. In dynamic

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explicit FEMs, the explicit time integration method is used, and the FE equations are solved by explicitly advancing the kinematic state from the previous increment, without iteration. Therefore convergence problems are not an issue. It is also suitable for parallel execution because the computations can be conducted at the element level. Recently, a GPU-based dynamic explicit FEM algorithm with total Lagrangian formulations [6] was implemented via highly parallel graphics hardware for nonlinear deformation analyses of soft tissues. One aim of the current study is to investigate the applicability of this method for fast quasi-static breast deformation simulations.

Nonlinear hyperelastic models have been widely used for describing breast tissues [2], [3], [6]. However, the material parameters used for breast deformation simulations are generally obtained from *in vitro* tests, which are commonly different from *in vivo* data. Therefore, the second aim of this study is to develop a material parameter identification method to estimate *in vivo* material properties of breast tissues in the context of nonlinear hyperelastic models.

2 Method

Like most biological soft tissues, breast tissues exhibit nonlinear, anisotropic and time-dependent response under large deformation [7]. When breast tissues are subjected to small deformations (less than 2-5%), conventional anisotropic linear elastic models are adequate to model their mechanical behavior. However, large deformations are often involved in clinical practice, such as surgery, mammographic examinations or during ultrasound scanning etc, and linear elastic models are no longer valid for these materials. Soft tissues under large deformation often experience large recoverable elastic deformation, therefore hyperelastic models have been widely used to model the nonlinear and anisotropic behavior of these materials. The constitutive behaviour of hyperelastic materials is defined in terms of strain energy potential. By using different forms of strain energy function, several hyperelastic models including the incompressible/nearly incompressible, viscoelastic, hyperelastic and anisotropic behavior of soft tissues have been implemented in the GPU-based dynamical FE program [6].

2.1 Constitutive Model

In this study a transversely isotropic hyperelastic model was chosen to model the anisotropic behavior of breast tissues, and the strain energy potential had the following form [6]:

$$\psi = \frac{\mu}{2}\left(\overline{I}_1 - 3\right) + \frac{k}{2}(J-1)^2 + \frac{\eta}{2}\left(\overline{I}_4 - 1\right)^2 \tag{1}$$

where μ denotes the initial shear modulus; $\overline{I}_1$ represents the first deviatoric strain invariant; k stands for the bulk modulus; J denotes the total volume change; η represents a material parameter with units of Pa; $\overline{I}_4 = \mathbf{a}_0 \cdot \overline{\mathbf{C}} \cdot \mathbf{a}_0$ stands for the pseudo-invariant of $\overline{\mathbf{C}} = J^{-2/3}\mathbf{C}$, $\mathbf{C}$ denotes the right Cauchy-Green strain tensor, and $\mathbf{a}_0$ is the preferred direction to present the transversely isotropic response. In the model, μ

and k can be determined from another two elastic parameters, Young's modulus E and Poisson's ratio v, through the relationships of $\mu = E/(2(1+v))$ and $k = E/(3(1-2v))$. If the preferred direction of a tissue can be pre-determined, e.g. it is much stronger in the z direction, so $\mathbf{a}_0 = [0,0,1]$, only three parameters, (E, v, η), are required to completely define this anisotropic model. If $\eta = 0$, Equation (1) becomes the well-known Neo-Hookean isotropic model.

2.2 Finite Element Model of Breasts

In breast deformation analyses, FEMs were used to calculate the displacement field that satisfied the applied boundary conditions and a given set of material parameters. Both static implicit FEM program (ANSYS) and dynamic explicit FEM programs (ABAQUS/Explicit and GPU-based dynamic explicit FE program) were employed for breast deformation simulations. The geometrical model for FE analyses was constructed by segmenting MR image volumes into different tissues and then meshed into tetrahedral elements with ANSYS in order to account for the irregular breast shape. The material type of each element was assigned according to the segmentation. The displacement boundary conditions were applied by constraining the surface nodes of the breast, which were extracted by registering the MR images of the compressed breast to the MR images of the uncompressed breast using a 3D non-rigid image registration method. The detailed description on how to produce a FE model of the breast can be found in Ref [1].

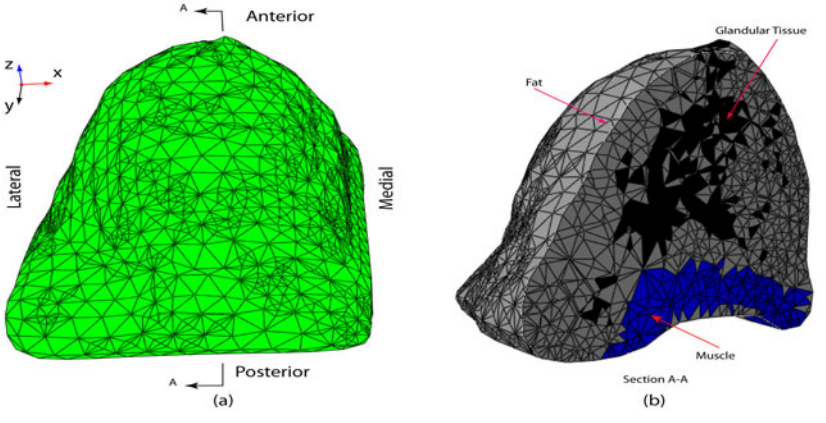

Fig. 1. A typical FE model: (a) Geometric model and FE mesh of undeformed breast (b) Distribution of breast tissues

Fig. 1(a) shows a typical geometric model and FE mesh of an undeformed breast, which will be compressed with a fixed medial plate and a moveable lateral plate. The breast compression by the two plates can be simulated by two approaches: (1) employ a contact model with/without friction effect to simulate the contact between the plates and the breast, and apply a displacement to the compression plates to compress

breasts; or (2) directly apply displacement boundary conditions to the breast surface on both medial and lateral sides to simulate frictionless contact between the plates and tissues, without using actual compression plates and contact definition. The second approach is simple and fast but may lead to unrealistic deformation, e.g. swelling on the surface [8]. At present, the contact model has not been implemented in the GPU-based dynamical FE program. Unless otherwise stated, all the breast compression simulations in this paper were performed by using the second approach to model the contact between the plates and the breast. As shown in Fig. 1(b), the breast is segmented into fat, fibroglandular tissue and pectoral muscle. This model consisted of 54025 4-node tetrahedron elements.

2.3 FE-Based Material Parameter Identification Method

The material parameters used for breast deformation simulations are generally obtained from *in vitro* tests, which are different from *in vivo* data. Therefore, an inverse algorithm was proposed to estimate the material parameters of *in vivo* breast tissues. Displacements of landmarks were estimated by image registration between the compressed and uncompressed MR images [1]. The material parameters that best fit the FEM predicted displacements to the estimated displacements of landmarks were found by solving a constrained optimization problem. The objective function was defined as:

$$\arg\min \left\| \mathbf{u}(\mathbf{p}) - \mathbf{u}_0 \right\|^2 \qquad \text{subject to } \mathbf{lb} < \mathbf{p} < \mathbf{ub} \tag{2}$$

where $\mathbf{p} = [E, v, \eta]^T$ was the material parameter vector with the lower bound constraint $\mathbf{lb}$ and upper bound constraint $\mathbf{ub}$; $\mathbf{u}(\mathbf{p})$ and $\mathbf{u}_0$ were the FE predicted displacements and the estimated displacements, respectively. The inverse problem was solved by using a hybrid simulated annealing algorithm. The global search was performed by use of the MATLAB function, *simulannelbnd,* to find parameter values near the optimum; then with these parameter values as initial values, the local search was performed by calling the MATLAB function, *fmincon*, at the end of iteration of the simulated annealing solver to find the optimization parameters. Since a number of iterations were involved in the inverse reconstruction of material parameters, it was not realistic to use a commercial FE program such as ABAQUS or ANSYS as an FE solver, particularly in case of 3D FE simulations with a typical CPU execution time of several hours. Therefore, due to its high speed execution, the GPU-based dynamic explicit FE program [6] was used as the FE solver in this study.

3 Results

The performance of the GPU-based explicit FE program on quasi-static deformation simulations of the breast was investigated by analysing the breast deformation under compression, as shown in Fig. 1. For comparison, the same FE model was also analysed by two commercial FE packages, ANSYS (static implicit FEM) and ABAQUS/Explicit (dynamic explicit FEM). To make the quasi-static deformation simulation valid when using explicit FEMs [5], the kinetic energy was monitored to ensure that the ratio of kinetic energy to internal energy was less than 5%; that is, the

dynamic effect could be neglected. Fig. 2 shows displacement distributions of the breast shown in Fig. 1(a) using three FE programs. The frictionless contact between the compression plates and the breast was simulated by applying a displacement boundary to the breast surface.

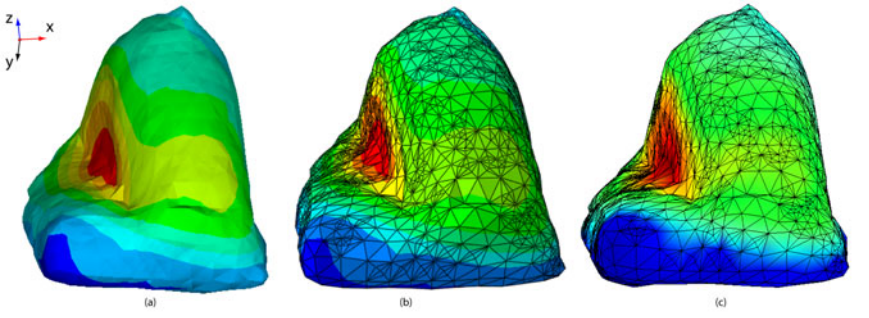

Fig. 2. Total displacement distributions calculated from (a) Static implicit FE (ANSYS 11.0) (b) Dynamic explicit FE (ABAQUS 6.8) and (c) Dynamic GPU-based FE program

As shown in Fig. 2, all three FE programs give a consistent displacement distribution. Although a large deformation (30% compression) was involved, the two explicit FE programs had no difficult converging, and unlike the implicit FE program, ANSYS, no intervention was required during simulation. However, an execution time of 15.6s with the GPU-based dynamic explicit FE program (run on a 2.4GHZ Intel Core 2 CPU PC with a NVIDIA GeoForce GTX280 1GB graphics card) was much less than an execution time of 6.0h with ABAQUS/Explicit (run on a 2.4GHZ Intel Core 2 CPU PC with an integrated graphics card). Much longer computation time and additional processing to handle convergence difficulties (through re-mesh and solution mapping procedures) were required to complete the same simulation using ANSYS.

The estimation of the property parameters of breast tissues was performed with the method described in Section 2.3. Seven FE models were created from the MR data of seven subjects (denoted as S1 to S7) before and after compressing the breast with two plates, following the method described in Section 2.2. For the sake of simplicity and avoiding unrealistic deformation due to partial constraints on the surface [8], all the surface nodes of the breast models were constrained by applying a displacement boundary condition directly extracted through registering deformed MR volume images to undeformed MR volume images of the breast. The GPU-based FE program was employed as a FE solver for breast compression simulations. In the FE-based reconstruction procedure, the material property parameters of fat, glandular tissue and muscle were considered as variables. Since only displacement boundary conditions were applied, the displacement field was determined by the relative values of the material property parameters of tissues. Here we chose fat as the reference material with an initial Young's modulus of 1kPa [1]. Both transversely isotropic and isotropic hyperelastic models were considered. For the anisotropic hyperelastic model, the variables included (v_f, η_f) for fat, (E_g, v_g, η_g) for fibroglandular tissue and (E_m, v_m, η_m) for muscle, and we assumed that the z direction was the preferred direc-

tion, $a_0 = [0,0,1]$. For the isotropic Neo-Hookean model, $\eta_f = \eta_g = \eta_m = 0$. The material parameters were estimated by minimising the difference between FE predicted displacements and estimated displacements computed via image registration at the landmark positions. That is, the estimated displacements at the landmarks were considered as ground truth. 80% of all nodes within the regions of glandular tissue and muscle were randomly chosen as landmarks. Fig. 3 shows typical outputs during the material parameter identification procedure for subject S1. Fig. 4 presents a comparison of deformed tissue structures from the image registration and the FE prediction by using optimized material parameters, as shown in Fig. 3(b).

The material parameter identification process was a process to find the best match of deformed internal tissues between the FE prediction and the estimation with image registration through optimising material property parameters. Table 1 1ists the mean

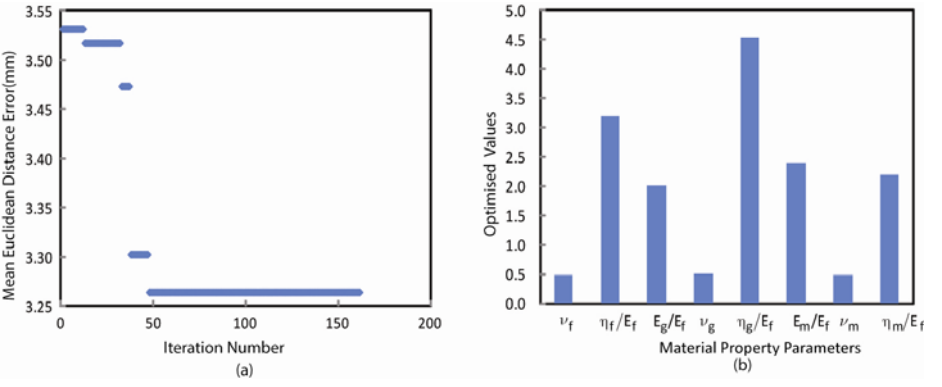

Fig. 3. Typical outputs in the material parameter estimation process for subject S1: (a) Error change with increasing iterations (b) optimized material property parameters

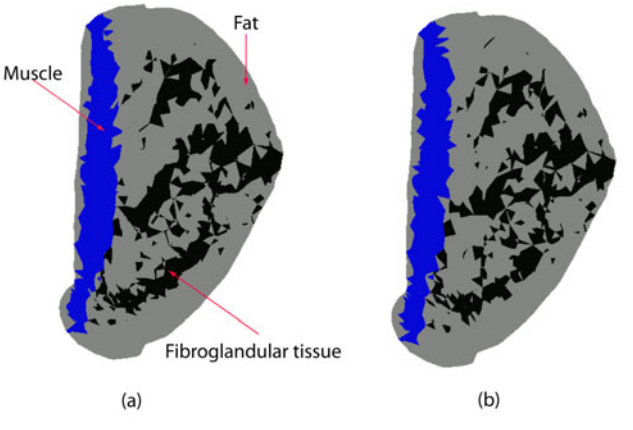

Fig. 4. Deformed tissue structures on the slice through the nipple: (a) Estimation from image registration and (b) FE prediction

Euclidean distance errors (or matching errors) after optimisation. Considering that the displacements of landmarks were estimated from image registration and registration errors can not be avoided, the GPU-based explicit FE program gave a reasonable prediction of internal tissue deformations. The results listed in Table 1 also show that the FE prediction accuracy could be improved by considering the anisotropic effect of breast tissues, although the performance improvement was limited (up to 10%). The limited performance improvement may lie in the fact that the tissues have less freedom to deform due to constraining all the surface nodes of the breast in this study. It is expected that the anisotropic effect of tissues will be more obvious when the contact model was directly used to simulate the breast deformation by compression plates, as shown in Fig. 5. ABAQUS/Explicit was used for these simulations. The contact between the breast and the compression plate was modelled by defining contact pairs on the surface. The optimised material parameters from the material parameter estimation process were employed for both the isotropic model and the anisotropic model. A clearly greater elongation in the z direction was observed from the isotropic model.

Table 1. Mean Euclidean distance error between FE predicted and estimated displacements at the landmark positions using different material models

Subject	Error using isotropic hyperelastic model (mm)	Error using anisotropic hyperelastic model (mm)	Performance Improvement
S1	3.518	3.263	7.2%
S2	2.945	2.935	0.45%
S3	2.086	2.038	2.29%
S4	3.015	2.79	7.36%
S5	2.122	2.076	2.12%
S6	4.583	4.238	7.51%
S7	3.635	3.271	10.0%

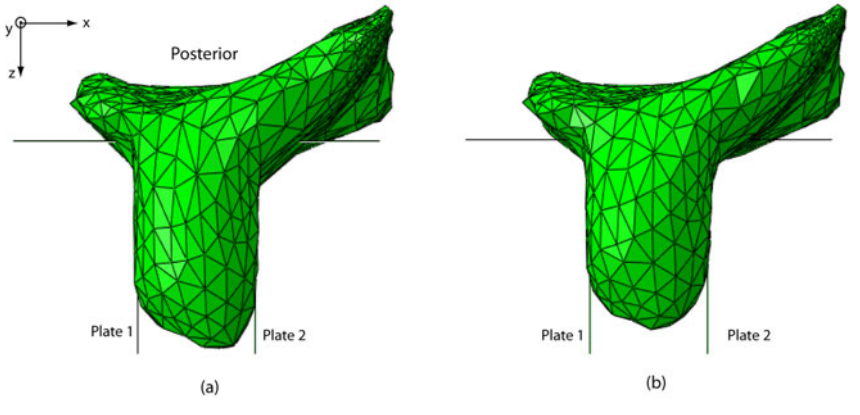

Fig. 5. Breast compression simulations of subject 3 using different material models: (a) Isotropic hyperelastic model (2) Anisotropic hyperelastic model

4 Discussion and Conclusion

The GPU-based dynamic explicit FEM algorithm developed was capable of simulating large nonlinear quasi-static deformations of breast tissues at high speed and there was no convergence difficulty.

By taking advantage of the high speed execution of the algorithm, a general material parameter identification method was developed to estimate the material property parameters of *in vivo* breast tissues. Since only displacement boundary conditions were considered, the material parameters obtained were relative values. However, the same method could be used to estimate real material property parameters by minimising the difference between predicted force-displacement response and experimentally measured force-displacement response. When anisotropic effects of soft tissues were included, the matching errors of internal tissue deformations between the FE prediction and the estimation by image registration decreased for all cases, showing that the anisotropic hyperelastic models provided more accurate simulations of breast deformations. This confirms a similar observation made for linear transverse isotropic materials [1].

Although the frictionless contact between compression plates and the breast can be simulated by applying surface displacement boundary conditions, it may lead to unrealistic deformation simulations on the surface [8]. To avoid this problem and facilitate wider applications such as surgery simulation, the contact model will be implemented into the GPU-based FE program to simulate the frictional/frictionless contact between soft tissues and medical equipment/devices in the future.

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References

1. Tanner, C., White, M., Guarino, S., Hall-Craggs, M.A., Douek, M., Hawkes, D.J.: Anistropic Behaviour of Breast Tissue for Large Compressions. In: 6th IEE International Symposium on Biomedical Imaging, pp. 1223–1226. IEEE Press, Boston (2009)
2. Carter, T.J., Sermesant, M., Cash, D.M., Barratt, D.C., Tanner, C., Hawkes, D.J.: Application of Soft Tissue Modelling to Image-guided Surgery. Med. Eng. Phys. 27, 893–909 (2005)
3. Pathmanathan, P., Gavaghan, D.J., Whiteley, J.P., Chapman, S.J., Brady, J.M.: Predicting Tumor Location by Modeling the Deformation of the Breast. IEEE Trans. Biomed. Eng. 55, 2471–2480 (2008)
4. ANSYS v.11, ANSYS Inc. (2007)
5. ABAQUS, ABAQUS Online Documentation: Version 6.8. HKS, Inc. (2008)
6. Taylor, Z.A., Comas, O., Cheng, M., Passenger, J., Hawkes, D.J., Atkinson, D., Ourselin, S.: On Modelling of Anisotropic Viscoelasticity for Soft Tissue Simulation: Numerical Solution and GPU Execution. Med. Image Anal. 13, 234–244 (2009)
7. Han, L.H., Noble, J.A., Burcher, M.: A Novel Ultrasound Indentation System for Measuring Biomechanical Properties of in vivo Soft Tissue. 29, 813–823 (2003)
8. Ruiter, N.V.: Registration of X-ray Mammograms and MR-Volumes of the Female Breast based on Simulated Mammographic Deformation. University of Mannheim, PhD Thesis (2003)