Virtual Environments for Medical Training: Soft tissue modeling

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의료용 훈련을 위한 가상현실에 대한 연구

김 정

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Abstract

For more than 2,500 years, surgical teaching has been based on the so called "see one, do one, teach one" paradigm, in which the surgical trainee learns by operating on patients under close supervision of peers and superiors. However, higher demands on the quality of patient care and rising malpractice costs have made it increasingly risky to train on patients. Minimally invasive surgery, in particular, has made it more difficult for an instructor to demonstrate the required manual skills. It has been recognized that, similar to flight simulators for pilots, virtual reality (VR) based surgical simulators promise a safer and more comprehensive way to train manual skills of medical personnel in general and surgeons in particular. One of the major challenges in the development of VR-based surgical trainers is the real-time and realistic simulation of interactions between surgical instruments and biological tissues. It involves multi-disciplinary research areas including soft tissue mechanical behavior, tool-tissue contact mechanics, computer haptics, computer graphics and robotics integrated into VR-based training systems. The research described in this paper addresses the problem of characterizing soft tissue properties for medical virtual environments. A system to measure *in vivo* mechanical properties of soft tissues was designed, and eleven sets of animal experiments were performed to measure *in vivo* and *in vitro* biomechanical properties of porcine intra-abdominal organs. Viscoelastic tissue parameters were then extracted by matching finite element model predictions with the empirical data. Finally, the tissue parameters were combined with geometric organ models segmented from the Visible Human Dataset and integrated into a minimally invasive surgical simulation system consisting of haptic interface devices and a graphic display.

1. INTRODUCTION

A Virtual Reality (VR)-based surgical simulation system [1], which provides an innovative tool for training medical personnel, requires accurate modeling of material properties, high fidelity organ geometry and fast computation algorithms to simulate the tissue deformation induced by a surgical instrument. While accurate organ geometry and computation algorithms have been widely studied [2], the characterization of tissue properties, especially *in vivo*, has not been sufficiently investigated due to the difficulty of the testing itself and of modeling the complexities of non-linearity and time dependency.

The material properties of various tissues have been measured ex vivo for decades [3]. However, ex vivo measurements may not be suitable for surgical simulation due to post mortem changes in tissues' mechanical properties. After removing

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samples from the body, the tissue's properties may change drastically from factors such as 1) temperature (which is likely to affect viscosity), 2) hydration (which can change both elasticity and viscosity), 3) protein oxidation or cross-linking (which can change stiffness), and 4) loss of blood pressure (which may affect elasticity and viscosity). Moreover, the boundary conditions of an ex vivo sample are different from those *in vivo*. Cutting tissue out of the organ may change the apparent force-displacement relationship. Owing to these concerns, it is desirable to measure the material properties of tissues in live animals (*in vivo*), within their body (in situ) and with specially designed instruments [4].

Fitting *in vivo* experimental data, particularly from indentation experiments, to a mechanical model required a different approach. The data from indentation experiments lacked many of the features that make ex vivo samples convenient to calibrate. Typically, the samples had non-uniform cross-sectional areas and non-uniform strain across any given cross section. An analytical solution based on the boundary value problem was not a good candidate, given the complexity of the material's behavior, the organ's geometry and the three-dimensional deformation imposed on the material's surface. To circumvent these difficulties, the inverse finite element estimation has been investigated for the characterization of soft tissue properties [5]. This method estimates unknown material parameters for a selected material law by minimizing the least-squares difference between predictions of a finite element model and experimental responses. This study uses the inverse finite element estimation method is used. This implementation combines a three dimensional finite element model with a nonlinear optimization algorithm to estimate material parameters by matching experimental results. This approach is used to determine *in vivo* material parameters of intra-abdominal tissues from ramp-and-hold indentations with a small radius circular tip. A shortened version of this paper was presented in 2006 at the Medical Image Computing and Computer Assisted Intervention (MICCAI) conference in Palm Springs, CA with the title, "Characterization of Viscoelastic Soft Tissue Properties from *In vivo* Animal Experiments and Inverse FE Parameter Estimation."

2. METHODS

2.1 *In vivo* tests on pigs' intra-abdominal tissues

Data were used from experiments conducted on intra-abdominal organs of pigs at the Harvard Center for Minimally Invasive Surgery, in collaboration with surgeons from the Massachusetts General Hospital (MGH) [6]. Ten pigs were used in these experiments and detailed information regarding the experiments, including that related to the instrumentation, protocol and data, can be found in a paper written by the same authors. Each pig was first put under general anesthesia and placed onto the surgical table. A midline incision into the abdomen was made and the abdominal cavity was dissected to expose the target organs. The static force responses and dynamic responses to the ramp-and-hold input were then measured (Fig. 1).

2.2 Material models

Nonlinearity and time-dependence were apparent in the organs' force responses (Fig. 1). Given that a linear elastic material law cannot model these nonlinearities, a more general material law should be used to describe this behavior. The quasi-linear viscoelasticity (QLV) framework proposed by Fung [3] was used for modeling. This approach assumes that material behavior can be decoupled into two effects: a time-independent elastic response and a linear viscoelastic stress-relaxation response. These models can be determined separately from the experiments. The stresses in the tissues, which may be linear or nonlinear, are linearly superposed with respect to time.

The three-dimensional constitutive relationship in the framework of QLV is given by

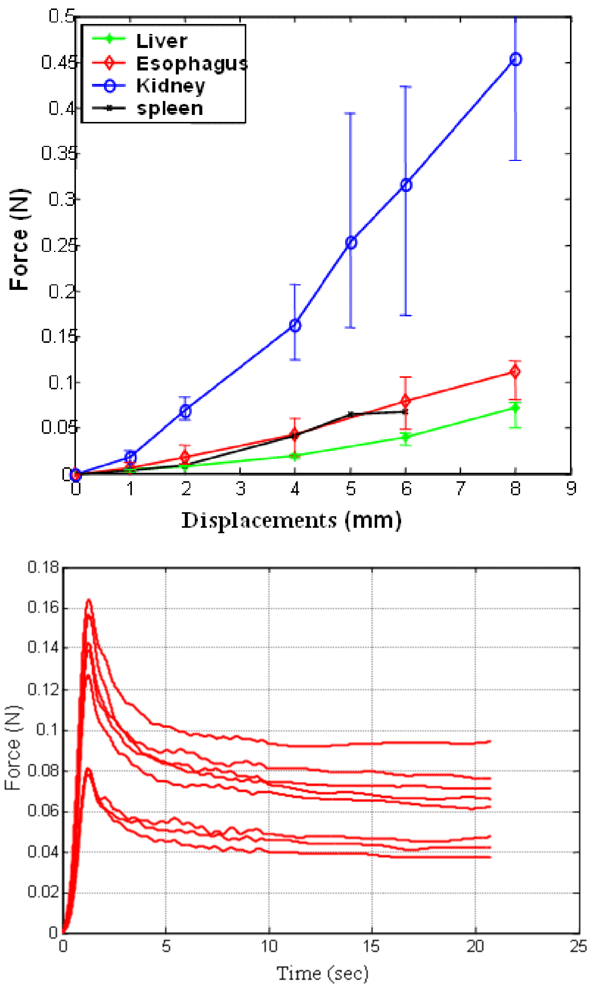

Fig. 1 (a) The static force responses of various intra-abdominal organs of pigs

(b) Typical force responses over time against various indentation depths

$$S(t) = G(t)S^e(0) + \int_0^t G(t-\tau)\frac{\partial S^e(E(\lambda))}{\partial \tau}d\tau \quad (1)$$

where S(t) is the second Piola-Kirchhoff stress tensor and G(t) is known as the reduced relaxation function. $S^e(E(\lambda))$ is termed the material's pure elastic response and can be nonlinear or linear.

The reduced relaxation function G(t) is a scalar function of time and often can be expressed by the Prony series,

$$G(t) = G_0\left(1 - \sum_{i=1}^{N} \overline{g}_i^P\left(1 - \exp\left(-\frac{t}{\tau_i}\right)\right)\right)$$
$$G_0 = G(0) \quad (2)$$

where the $\overline{g}_i^P$ s are the Prony series' parameters.

For the nonlinear elastic response, an incompressible hyperelastic material representation is used; this is commonly used for elastomer modeling. A hyperelastic material's properties can be determined by the strain energy function (W). Ideally, W is defined with only as many parameters as are required in order to make an FE model. Many specific material models could be used, depending on how we want to approximate the strain energy function. Two models are selected for use here: the neo-Hookean model and the Mooney-Rivlin model, both of which are widely used in soft tissue simulations.

The strain energy function of the three-dimensional incompressible Mooney-Rivlin model is given

$$W = C_{10}(I_1 - 3) + C_{01}(I_2 - 3) \quad (3)$$

where C_{10} and C_{01} are material parameters (having units of stress), and I_1 and I_2 are principal invariants. If the dependency of the second invariant term's dependency is neglected, it is possible to obtain another widely used material model, termed the neo-Hookean model.

$$W = C_{10}(I_1 - 3) \quad (4)$$

As an analytical solution considering the above material law and experimental conditions is elusive, the Finite Element Method (FEM) [7] has been widely used in simulations. Modeling the indentation experiments with the QLV approach can express the FE simulation's outcome simply as

$$F_s = FEM\_SIMULATION(p_i)$$
$$p_i = [\tau_i, g_i, C_{ij}] \quad (5)$$

where F_s is the simulated force and p_i is the material parameter containing the viscoelasticity and nonlinear elasticity. The goal of this characterization is to determine these parameters for a proposed material law by minimizing the errors between the simulated and the associated experimental measurements. This process is also known as the inverse calculation, because it is the opposite of an

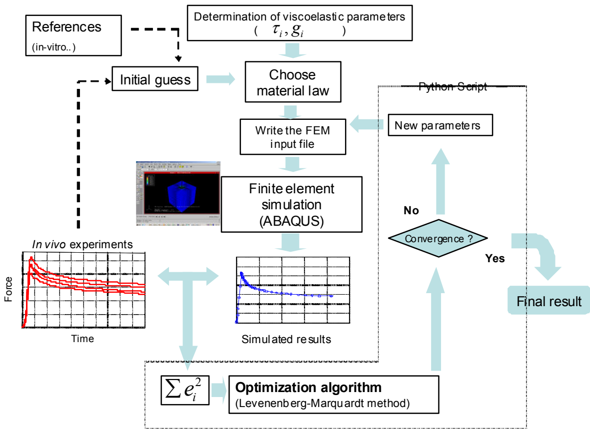

Fig. 2 Flow chart for the inverse FEM parameter estimation algorithm

ordinary simulation (that is, solving for forces or displacements given material parameters and boundary conditions).

Instead of estimating all required parameters in a single step, the characterization process was separated into two stages. The first step determined the viscoelastic parameters from the normalized force response against the ramp-and-hold indentation. With the viscoelastic parameters estimated in the first stage, the inverse FEM parameter estimation method was used to determine the remaining elastic parameters as shown Fig. 2.

2.3 Determination of the viscoelastic parameters

This section develops a three-dimensional linear viscoelastic model of the soft tissue based on the force-displacement experimental data. In linear viscoelasticity, the Laplace transformed Hooke's law takes the form [8]

$$\bar{\tau}_{ij}^{d}(s) = 2s\bar{G}(s)\bar{\varepsilon}_{ij}^{d}(s),$$
$$\bar{\tau}_{kk}(s) = 3s\bar{K}(s)\bar{\varepsilon}_{kk}(s), \quad \{i,j,k\} \in \{1,2,3\} \quad (6)$$

Here, $\bar{\tau}_{ij}^{d}(s)$ and $\bar{\tau}_{kk}(s)$ represent, respectively, the Laplace transformed deviatoric and volumetric components of the Cauchy stress tensor. Similarly, $\bar{\varepsilon}_{ij}^{d}(s)$ and $\bar{\varepsilon}_{kk}(s)$ represent the Laplace transformed deviatoric and dilatational strain tensor components. $\bar{G}(s)$ is the step response rigidity modulus and $\bar{K}(s)$ is the step response bulk modulus. "s" is the Laplace transform variable.

The simplest lumped parameter model that can capture a solid's viscoelastic behavior is the three-parameter linear solid model, whose transfer function can be written as

$$\frac{F(s)}{\delta(s)} = F_{ss}\prod_{i=1}^{n}\left(\frac{1+\alpha_i \tau_i s}{1+\tau_i s}\right) \quad (7)$$

where $F(s)$ and $\delta(s)$ are the Laplace transformed force and displacement variables, respectively; F_{ss} is the force response's steady state value; τ is the relaxation time constant; and α is the ratio of the system's initial response to a step in displacement to the steady state value (α >1). Incidentally, this model is also known as the Kelvin model. The point indenter is a good choice for the model parameter estimation, as it is the closest approximation of a punch on an elastic half space.

From linear elasticity, it is known that the total force, P, required when indenting a frictionless circular cylindrical punch of radius a into an isotropic elastic half space by a distance D is given by

$$P = \frac{8aG(G+3K)}{4G+3K}D \quad (8)$$

where G is the rigidity modulus and K is the bulk modulus. The correspondence principle may now be invoked to obtain the corresponding quasistatic viscoelastic solution of a flat-faced circular cylindrical punch indenting a viscoelastic half space

$$P(s) = \frac{8as\bar{G}(s)(\bar{G}(s)+3\bar{K}(s))}{4\bar{G}(s)+3\bar{K}(s)}D(s) \quad (9)$$

where $\bar{G}(s)$ and $\bar{K}(s)$ are the step response rigidity and bulk moduli, respectively. The implication of assuming a nearly incompressible tissue is that the bulk modulus is very large compared to the rigidity modulus. Hence, the material primarily relaxes in the deviatoric mode. This assumption allows the simplification of Eq. (9) to

$$P(s) = 8as\bar{G}(s)D(s) \quad (10)$$

From Eqs. (7) and (10), the step response rigidity modulus can be written as

$$\overline{G}(s) = \frac{F_{ss}}{8as}\prod_{i=1}^{2}\left(\frac{1+\alpha_i\tau_i s}{1+\tau_i s}\right) \tag{11}$$

The inverse Laplace transform of Eq. (11) is written as

$$G(t) = (k_0 + k_1 e^{-t/\tau_1} + k_2 e^{-t/\tau_2}) \tag{12}$$

2.4 Inverse FEM parameter estimation using the optimization algorithm

The application in this study compares the simulated forces from the FEM simulation to the associated experimental forces at the indenter. Therefore, it is possible to minimize a nonlinear sum of squares given by

$$E = \sum_{i=1}^{m}(F_s(t_i) - F_e(t_i))\cdot(F_s(t_i) - F_e(t_i))$$

$$t_i = (t_i, t_2, \cdots, t_m) \tag{13}$$

where F_e, F_s, t_i and m are measured forces, simulated forces, time and the total number of data points, respectively. Among several optimization algorithms that could be used, the nonlinear least square optimization known as the Marquardt-Levenberg algorithm is adopted. It updates the parameters iteratively depending on the norm of $J^T J$ and the Marquardt parameter λ.

$$H = (J^T J + \lambda I)^{(i)}$$

$$\Delta\vec{p} = -H^{-1}[J^T \cdot (f_s(\vec{p}^{(i)}) - f_e)]$$

$$\Delta\vec{p} = \vec{p}^{(i+1)} - \vec{p}^{(i)}$$

$$J = [\frac{\partial F_s}{\partial p_1}, \frac{\partial F_s}{\partial p_1}\cdots] \tag{14}$$

Here, $\vec{p}^{(i)}$ is a vector containing the estimated parameters and J is the Jacobian vector for the corresponding iteration (i). As the parameters are contained implicitly in the FEM simulation, the Jacobian vector J should be computed numerically with respect to each parameter variation. This procedure can be repeated until the difference becomes smaller than a certain tolerance value.

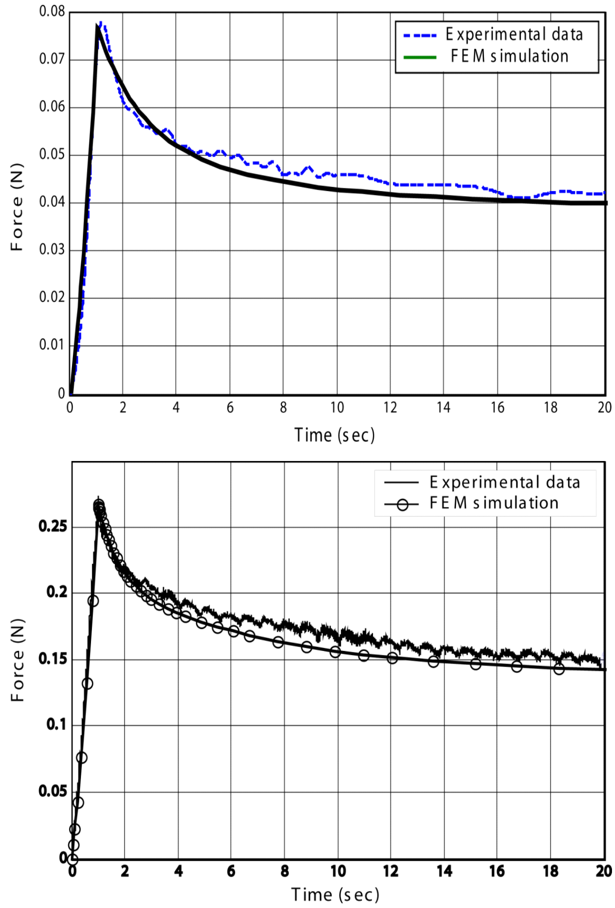

Fig. 3 Force responses of the FE simulation and the experiments: a) liver with a 5mm indentation, b) kidney with a 6mm indentation. The data from the experiment were filtered out to remove noisy properties using a 3rd order Butterworth filter. The responses in (b) show this noisy signal from the experiments.

3. RESULTS

The simulation was performed on a WinNT Pentium III 3.3 GHz workstation. Two force profiles measured from the liver and kidney used in the experiments were selected. The viscoelastic parameters were estimated from these normalized profiles and were input into the ABAQUS database for viscoelastic modeling. Because a rough but reasonable initial guess was required for the organ's elastic parameters, their static force responses were

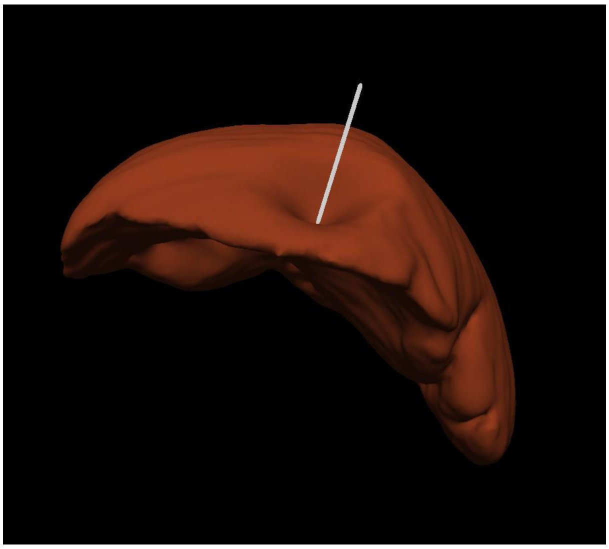

Fig. 4 A snapshot of organ palpation simulation for medical simulators

used. With these approximate initial values, the Python code was used to iterate the FE model and update the parameters automatically. The parameters reached convergence after four or five iterations.

Fig. 3 shows the predicted forces from the FE simulation with the estimated parameters and experimental forces for the pig liver and kidney. The force responses of the hyperelastic model in ABAQUS match the experimental data well. The soft tissue parameters obtained here have been integrated into a real time organ model for a surgical simulator as shown Fig. 4. The organ model has 1KHz force update frequency and 30 Hz visual frame update rate.

4. CONCLUDING REMARKS

This paper characterizes intra-abdominal organs' mechanical properties by the inverse FEM parameter estimation. The viscoelastic and hyperelastic material parameters were estimated in two stages in the framework of the QLV. To calibrate the parameters to the experimental results, a three-dimensional FE model was developed to simulate the forces at the indenter, and an optimization program was also developed that updates new parameters and runs the simulation iteratively. Key assumptions in this approach are that the organs are incompressible, homogenous and isotropic; and that the deformations imposed are small compared to the organ's size. The inverse FEM technique can be extended easily to include more general features of soft tissue behavior, if necessary. The approach may be extended to increasingly complex organs by building layered organ models and estimating each layer's material properties with this algorithm.

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