Parameter Estimation for a Mechatronic Probe of Robot assisted Minimally Invasive Surgery Using Inverse Finite Element Analysis

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Abstract

There is a need to provide haptic and tactile feedback to surgeons during robot-assisted minimally invasive surgery (RMIS). Such feedback is also essential for palpation based diagnostic during cancer removal using MIS. There have been recent efforts at developing a mechatronic finger to mimic some of the palpation capabilities of a human finger. These mechatronic fingers typically record force-displacement characteristics, in order to infer material properties for diagnostic purposes. This paper presents a non-linear finite element based approach for tissue property identification, based on force-displacement characteristics produced by a mechatronic finger, during mechanical palpations. We use finite element modeling and the Newton-Raphson method to estimate soft tissue parameters. To obtain the ground truth data, a sphere-soft tissue indentation experiment is conducted on a silicone phantom and the sphere-tissue interaction is modeled using finite element software ABAQUS^{TM}. To account for the large deformation behavior of the soft tissue, the Arruda-Boyce hyperelastic model is chosen. Then inverse finite element analysis and the Newton-Raphson method is employed to identify the shear modulus (μ) of the hyperelastic model, employing the static sphere-tissue indentation data as input. The results show that the proposed method can identify soft tissue parameters accurately and robustly with a relatively fast convergence rate. The force-tissue deflection curves predicted by the identified soft tissue parameter are in good agreement with experimental measurements.

Keyword: Inverse finite element analysis, Medical tool, Soft tissue, Newton-Raphson method

1. Introduction

This paper presents work carried out to identify the unknown mechanical properties of a biological soft tissue using sphere indentation load-displacement data.

In-vivo tissue property identification is vitally important during surgical procedures, and surgeons use tactile sensing to identify malignant tissue. However, with robot assisted minimally invasive surgery (RMIS), tactile feedback is generally not available. The loss of tactile feedback is a significant disadvantage in MIS, which prevents the surgeon from directly palpating specific tissues and potentially leads to operative error. This sensory reduction is only partly compensated for by employing improved optics with high magnification during MIS. Recent proposals by the authors on a wheeled indenter which can perform dual modalities: static tissue indentation and rolling tissue indentation illustrates the potential for performing an investigation on the mechanical properties of actual tissues [1, 2].

In order to conduct such an investigation in a precision manner, a method for tissue mechanical properties estimation via sphere-tissue interaction is demanded to work in conjunction with the physical device. In this paper, the work on tissue parameter estimation using the static sphere-tissue indentation modality is described. A procedure based on inverse finite element analyses and the Newton-Raphson method is developed to perform this task and is validated through the uniaxial compression experiments on a silicone phantom (RTV6166, General Electric) which has similar mechanical properties of biological soft tissue [3].

2. Background

2.1. Tissue Properties

Nonload-bearing biological soft tissues are well known for their highly nonlinear characteristics and viscoelasicity. Many soft tissues are anisotropic, heterogeneous, nearly incompressible, with a porous internal structure, and variable mechanics depending on the environment such as pH value, temperature, health etc. Due to their viscoelastic nature, when held at constant strain, they show stress relaxation. When held at constant stress, they show creep. Their stress-strain relationship is incrementally nonlinear with strain. They exhibit hysteresis loops in cyclic loading and unloading. Under repeated cycles, they show preconditioning which is a steady state, where the stiffness and hysteresis stabilize in successive cycles. The biomechanics of soft tissue is time and strain rate dependent [5, 8]. They are difficult to be characterized due to their inherent complexity, the degradation of mechanical properties after death and poorly known boundary conditions [4, 5].

There is evidence [4, 5, 6, 7,] indicating that a significant correlation exists in mechanical characteristics between tissues of different pathological states. Hence, to use wheeled indenter–tissue interaction dynamics to classify mechanical tissue properties and consequently identify the location and characteristics of malignant tissue is an important tool for tissue diagnosis.

In vitro experiments were conducted by researchers from Edinburgh to examine the relationship between the morphology and the mechanical properties of prostatic tissues, and develop a technique for diagnosis of benign prostatic hyperplasia (BPH) [4, 5, 6, 7,]. The tissue specimens were collected from patients undergoing transurethral resection of the prostate (TURP) for benign or malignant prostatic enlargement. An indentation device was used to measure the shear modulus of tissue specimens. The results showed that measurable differences exist between the mechanical characteristics of benign and malignant prostatic tissue and provided further evidence that significant correlations exist between prostatic tissue morphology and mechanical characteristics [4,5,6,]. Additionally, [7] reported that there exists a statistically

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significant reproducible difference in stiffness between tumour tissue and normal healthy tissue when they measured prostate tissue using a resonance sensor.

2.2. Minimally Invasive Surgery

In its simplest terms, MIS, or laparoscopic surgery, can be described as major or minor surgery performed through small incisions. A fibre optic camera is passed through such an incision to provide the surgeon with a field of view, and various laparoscopic instruments are inserted through one or two other incisions to perform the procedure. The primary benefit of this approach is that the use of small incisions results in less trauma for the patient [4], thus decreasing recovery time and hospitalisation costs. However, these advantages are offset by the sharp increase in the technical difficulty of any surgical procedure carried out using MIS. Due to the fact that the procedure is performed from outside the body, the surgeon's ability to both see and touch the operating environment is reduced. These problems are compounded by the fact that distal dexterity is also impaired due to use of long, rigid instruments introduced through a fixed point. Even simple point-to-point movements require extensive training as directions are reversed in-vivo [5]. This reduction of visual, haptic and tactile feedback coupled with dexterity problems can lead to accidental damage of tissue [6]. Furthermore, when performing delicate procedures such as beating heart surgery, the destabilisation induced by respiratory and cardiac motion affects tissue-instrument interaction [7].

2.3. Robot-assisted Minimally Invasive Surgery

Recently, a number of surgical robotic systems have been developed with attempts to overcome the problems of traditional MIS. These include commercialized computer-integrated systems such as the Zeus™ Surgical System from Computer Motion, Inc. [9] and the da Vinci™ Surgical System from Intuitive Surgical, Inc. [10]. Both are master-slave robotic systems which have four robotic arms to manipulate the surgical tools precisely in the surgical site under surgeon tele-operated control. Since the distinct advantages of the robotic systems are the ability to scale down hand movements, filter tremors, and eliminate problems due to the impairment of hand-eye coordination caused by the fulcrum effects, they provide better surgical outcomes. In addition to these, improvements based on 3D vision and high distal dexterity tools also allow complex surgical procedure such as coronary artery bypass grafting [11] and mitral valve repair [12], which are usually difficult to conduct by conventional minimally invasive means, however, the lack of haptic feedback is still one of the major downsides of current robotic surgical systems.

2.4 Finite Element Techniques

Many researchers have used FE techniques to simulate soft tissue behaviour and apply this technique for soft tissue parameter identification [13, 14, 15, 16]. Tillier et al. applied hyper-elastic constitutive equations using finite element software ANSYS to identify tissue properties from experimental measurement [13]. The method was applied on lamb kidney and human uterus, and the stimulation results agreed with experiment data. Liu et al. [14] also applies a nonlinear hyper-elastic 8-chain network (Arruda-Boyce model) constitutive law to model soft tissue undergoing large indentations by using ABAQUS software, to identify two material parameters, the initial modulus and locking stretch. Kerdok et al. used ABAQUS to identify the properties of breast tissue base on Arruda-Boyce constitutive law [15]. Zhang et al [16] used a Finite element (FE) model to simulate large tissue deformations. Tonuk et al [17] used FE analysis to simulate force-displacement' indentation behaviour of residual limb tissue. Picinbono et al [18] proposed a FE model for soft tissue deformation estimation based on nonlinear elasticity and anisotropic behaviour. Zhong et al [19] presented a methodology for predicting the deformations of soft objects, based on the analogy between heat conduction and elastic deformation. Szekely et al [20] developed a framework for full-scale FE simulation of elastic tissue deformation in complex systems such as the human abdomen. Schwartz et al [21] extended the linear elastic tensor-mass method to simulate biological soft tissue for planning surgical treatment of liver cancer. Duysak et al [22] used a spring-mass system to simulate facial soft tissue deformation during lower jaw bone realignment.

3. The Algorithm of Inverse FE Modelling and Newton-Raphson Method

3.1. Finite Element Modeling using ABAQUS

To study the soft tissue indentation, a silicone tissue phantom was modeled using the finite element software package ABAQUS 6.8-1, Fig. 3 - 6.

In this paper, nonlinear hyperelastic theory is applied and the material parameters are assumed to be non-linear, incompressible and isotropic. Hyperelastic materials are described in term of a “strain energy potential”, U(ε), which defines the strain energy stored per unit of volume as a function of the strain at that point in the material. There are several forms of strain energy potentials available in ABAQUS to model the approximately incompressible isotropic material and the Arruda-Boyce form has been selected for predicting the behaviour of natural soft tissue [2] The Arruda-Boyce strain energy potential is given by [23]:

$$U = \mu \sum_{i+1}^{5} \frac{C_i}{\lambda_m^{2i-2}} \left(I_1^i - 3^i \right) + \frac{1}{D} \left(\frac{J_{el}^2 - 1}{2} - \ln J_{el} \right) \tag{1}$$

Where

$C_1 = \frac{1}{2}, C_2 = \frac{1}{20}, C_3 = \frac{11}{1050}, C_4 = \frac{19}{7000}, C_5 = \frac{519}{673750}$

U	is the strain energy
μ	is shear modulus
λ_m	is locking stretch
D	is temperature
J_{el}	is the elastic volume ratio

I_1 is the first deviatoric strain invariants define as [23]

$$I_1 = \lambda_1{}^2 + \lambda_2{}^2 + \lambda_3{}^2 \tag{2}$$

λ_1, λ_2 and λ_3 are the principal stretches, which are the ratios of current length and the length in the original configuration in the principal directions of a material fiber. The principal stretches, λ_i, are related to principal nominal strain, ε, by

$$\lambda_1 = 1 + \varepsilon \ , \ \ \lambda_2 = \lambda_3 = \frac{1}{\sqrt{\lambda_1}} \tag{3}$$

The locking stretch, λ_m is the value of chain stretch when the chain reaches it’s fully extension before break. It can be measured from the simple tension or compression experiment in which the assumption of incompressibility is made ($\lambda_1 \lambda_2 \lambda_3 = 1$).

$$\lambda_{chain} = \frac{1}{\sqrt{3}}\left(\sqrt{\lambda_1^2 + \lambda_2^2 + \lambda_3^2}\right) = \frac{l}{l_0} \tag{4}$$

where λ_{chain} is the chain stretch, l is the current chain length, and l_0 is the initial chain length.

In this study, two parameters μ and λ_m are required for describing the nonlinear hyperelastic behavior, based on the Arruda-Boyce model. However, for uniaxial deformations the soft tissue is a fully incompressible material, J_{el} equal to one and therefore the second term is eliminated [23].

As the value of locking stretch, $\lambda_{m,}$ can be approximated as described above, only the shear modulus, μ, need to be identified to obtain the force deflection curve. Hence the inverse Newton Raphson method is used to identify the shear modulus, μ.

3.2 Newton-Raphson inverse analysis Method

The Newton Raphson method works by modifying an initial guess and arrives at a converged solution in an iterative manner [24]. The Newton Raphson method is developed from the Taylor series expansion:

$$f(x_{i+1}) = f(x_i) + f'(x_i)(x_{i+1} - x_i) + \frac{f''(\xi)}{2!}(x_{i+1} - x_i)^2 \tag{5}$$

Where ξ lies somewhere in the interval from x_i to x_{i+1}. An approximate version is obtained by truncating the series after the first derivative term:

$$x_{i+1} = x_i - \left(\frac{f(x_i)}{f'(x_i)}\right) \tag{6}$$

The present analysis utilizes the Newton-Raphson method to estimate unknown material properties. In this study, wheel-tissue indentation experiments were conducted on a silicone phantom. The soft tissue unknown parameters were identified by matching the predicted force-tissue displacement curve with experimental results. The proposed algorithm is illustrated by the flow chart shown in Figure 7. In the parameter identification scheme, the residual is defined as the difference between the measured value, F_T and the identified value, F_M and e is the error associated with data;

$$e = \frac{1}{n}\sum_{j}^{n}(F_T - F_M)^2 \tag{7}$$

The Newton-Raphson method minimizes the error function, e, with respect to the parameter, P:

$$P_{i+1} = P_i - J^{-1}\left[e_1(p_1, i_1)\right] \tag{8}$$

where $J = \left[\dfrac{\partial e_1}{\partial P_1}\right]$

An FE analysis of indentation was performed to obtain the force-displacement relation curves, F_M, in Fig. 2. The resulting curve is then compared with the measured one, F_T, and the error is calculated using equation (7).

The inverse analysis starts with two initial guesses of μ_0 and μ_1, and the value of the μ at kth iteration can be found by applying equation (9):

$$\mu_{k+1} = \mu_{k-1} - \left(\frac{\mu_{k-1} - \mu_k}{e_{k-1} - e_k}\right)e_{k-1} \tag{9}$$

4. Tissue Parameter Estimation via Normal Indentation

The use of an inverse finite element and the Newton-Raphson method, for tissue parameter estimation, was preliminarily carried out using a homogeneous silicone block (15×15×15 mm^3 homogeneous cubes). As shown in Fig. 1, during the test, a spherical indenter with 8 mm in diameter was used to indent into the center of silicone surface, by 6 mm with 1 mm/s of speed rate, and the curve of force deflection was recorded as shown in Fig.2.

Fig. 1 The experiment test for sphere probe indentation.

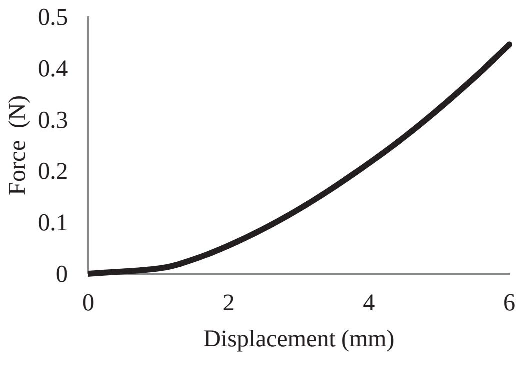

Fig. 2 The force-displacement curve from indentation experiment measured.

To estimate the tissue parameters, first a finite element model of the above experiment was developed. The 3D of silicone model was created as a deformable model on ABAQUS software with dimension of 15x15x15mm^3. Its mesh consists of 680 elements of 8-node linear brick, reduced integration and hourglass control (ABAQUS's element, C3D8R), assuming isotropic, incompressible, hyperelastic material with geometrical nonlinearity. The indenter was created as a sphere shape with the diameter of 8 mm by using "revolve component" on ABAQUS software, assuming analytical rigid with not necessary to meshing, as shown as Fig. 3.

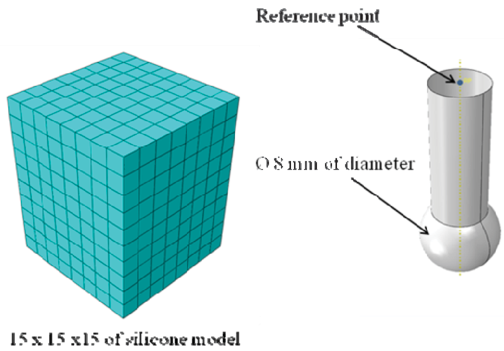

Fig. 3 The finite element model of silicone and indenter.

Fig. 4 The assembly between silicone model and indenter.

Afterward, the indenter and silicone model are assembled together as shown as Fig. 4, and the contact between them was using "frictionless contact". The bottom of the silicone model was fixed to the ground. Then, the 6 mm of displacement was applied at the reference point into the silicone model with 1 mm/s of speed rate showing as Fig.5, Fig.6. The force deflection recorded.

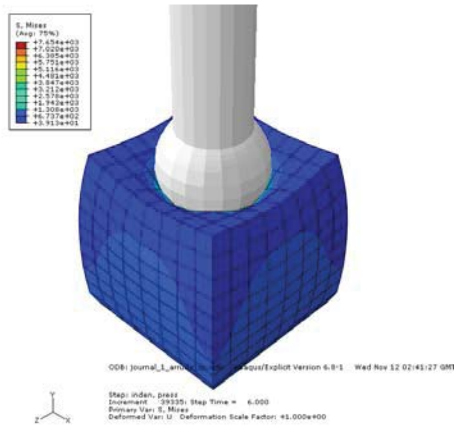

Fig. 5 The finite element model for silicone indentation.

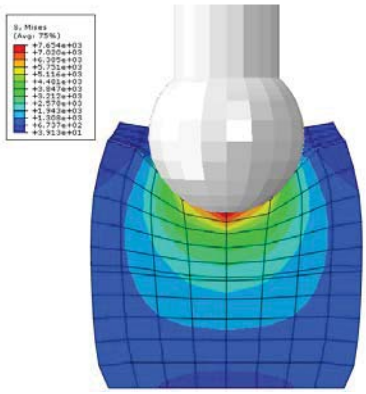

Fig. 6 A cross section of finite element model for silicone indentation.

The theory of the Newton-Raphson method is based on minimizing the error between the prediction results and measured data to identify the best fit unknown parameters. In Arruda-Boyce equation, two parameters, μ and λ_m, are required for describing the nonlinear hyperelastic behavior.

The locking stretch, λ_m, is the value of chain stretch when the chain reaches its full extension before breaking. It can be measured from a simple tension or compression experiment, assuming the material incompressible is made ($\lambda_1 \lambda_2 \lambda_3 = 1$) [15];

From equation (4), where λ_{chain} is the chain stretch, l is the current chain length, and l_0 is the initial chain length. Under a uniaxial compression test, we found that the locking stretch was reached, when the normal strain was 40% ($\lambda_1 = 0.6$). Therefore the locking stretch was calculated as $\lambda_m = 1.1$.

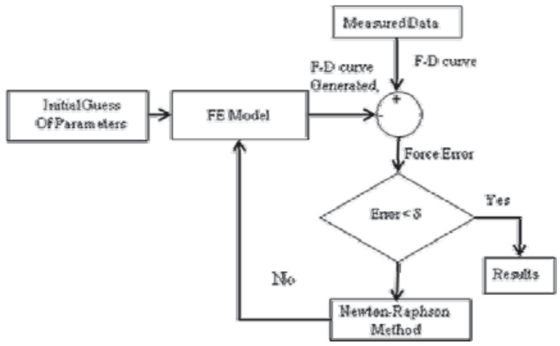

Fig. 7 A flow chart diagram of the inverse finite element model for parameter estimation.

The inverse analysis starts with two initial guesses, μ_0 and μ_1, for the unknown parameter. The resulting FE curve, F_m is compared with the measured one, F_T, and the error is calculated using equation (7). This is performed iteratively using the aforementioned inverse procedure (eq.9), until the solution converges. Since the method needs to start with two initial guesses μ_0 and μ_1, in this work, six sets of (μ_0, μ_1) were chosen as the initial guesses for the simulations and the force-displacement curves were record. An iterative solution consisting of each step requires approximately 3 minutes of computational time on a 2.8 GHz Pentium(R) D machine with 3.5GB of RAM.

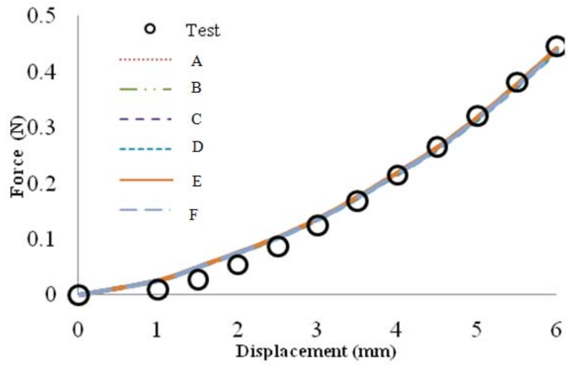

Fig. 8 The force-displacement curve generated from ABAQUS software with the six sets of initial guesses.

Table 1 Eleven sets of input from Newton-Raphson method compare to experiment result.

Initial Guess (kPa)	Estimated μ (kPa)	Prediction Error (%)
A. μ_0=0.1,μ_1=0.05	1.354	0.01
B. μ_0= 0.5,μ_1=0.2	1.355	0.01
C. μ_0=1.0,μ_1=0.1	1.359	0.01
D. μ_0=2.0,μ_1=1.8	1.340	0.01
E. μ_0=3.0,μ_1=1.2	1.359	0.01
F. μ_0=4.0,μ_1=3.0	1.348	0.01

Fig. 8 shows the estimation results when these initial guesses are used. Table 1 also shows the errors of predicted forces (using the estimation results) when compared to the measured forces. It is seem that the estimation results and computational speeds depend on the initial guesses used.

In order to validate the inverse finite element based parameter estimation method, the estimated results are compared with the experimentally measured data. A uniaxial compression test is carried out using an INSTRON 5543 machine, show as Fig.9, and a silicone cube with the dimension of 15x15x15 mm^3 was compressed by 6 mm at a speed of 1 mm/sec. The machine provided the stress-strain curve of the silicone sample and by curve fitting using Arruda-Boyce constitutive equation, the shear modulus μ was identified as 1.3 kPa.

Fig.9 The uniaxial compression test using the INSTRON machine 5543.

Table 2. The parameter predication error using Newton-Raphson inverse finite eleven method.

Initial Guess (kPa)	Estimated μ (kPa)	Estimation Error %	No. of Iterations	Computation time (min)
A. μ_0=0.1,μ_1=0.05	1.354	4.1538	1	3
B. μ_0= 0.5,μ_1=0.2	1.355	4.2308	1	3
C. μ_0=1.0,μ_1=0.1	1.359	4.5385	1	3
D. μ_0=2.0,μ_1=1.8	1.340	3.0769	1	3
E. μ_0=3.0,μ_1=1.2	1.359	4.5385	3	9
F. μ_0=4.0,μ_1=3.0	1.348	3.6923	1	3

Table 2 shows the parameter prediction error from the inverse finite element method. It is seem that, the Newton-Raphson method takes only a few iterations to converge for a range of initial gausses. The errors between estimates and measurements are less than 5% showing good performance of the proposed algorithm.

5. Conclusion and Future Work

This paper presents a method to identify the shear modulus of the silicone gel based on inverse finite element analyses and the Newton-Raphson method. To measure the silicone parameter, experiments was conducted on a silicone model (RTV6166, General Electric) which has similar mechanical properties of biological soft tissue. The shear modulus, μ. of Arruda-Boyce constitutive equation was used for finite element modelling. The Newton-Raphson method is used for estimation, using force and displacement curves from finite element model and experiment data. The results show that the method can identify of soft tissue parameter accurately and robustly with relatively fast speeds. The force tissue deflection curve generated from the identified soft tissue parameter is in a good agreement with the experimental measurement.

Future work will focus on the online parameter estimation, meanwhile additional work will be carried out to extend the one-parameter identification to two-parameter identification which includes the locking ration “λ_m”.

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7. References

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