Large Deformation Characterization of Mouse Oocyte Cell Under Needle Injection Experiment

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ABSTRACT

In order to better understand the mechanical properties of biological cells, characterization and investigation of their material behavior is necessary. In this paper hyperelastic Neo-Hookean material is used to characterize the mechanical properties of mouse oocyte cell. It has been assumed that the cell behaves as continuous, isotropic, nonlinear and homogenous material for modeling. Then, by matching the experimental data with finite element (FE) simulation result and using the Levenberg–Marquardt optimization algorithm, the nonlinear hyperelastic model parameters have been extracted. Experimental data of mouse oocyte captured from literatures. Advantage of the developed model is that it can be used to calculate accurate reaction force on surgical instrument or it can be used to compute deformation or force in virtual reality based medical simulations.

KEYWORDS

Biological cells, Levenberg–Marquardt optimization algorithm, Inverse finite element, Hyperelastic material

1. INTRODUCTION

Studying of biological cells behavior is very important and can help to diagnose disease with different mechanical properties. For example, the progression of the disease state of Malaria infected red cell by micropipette aspiration experiment has been reported in [1] and it has been observed that with progression of the disease, the rigidity in the cell has been increased.

Many researchers have been investigating the mechanical properties of biological cells and many experiments have been developed. Some of these experiments which have been done on biological cells are cell injection or cell indentation [2], micropipette aspiration [3], laser/optical tweezers [4], magnetic twisting cytometry [1], AFM indentation [5] and fluid shear flow [1].

These different experimental techniques have led to many mechanical models which constructed by various researchers; such as liquid drop models, spectrin network model for erythrocytes ,cytoskeletal models for adherent cells, solid models, fractional derivative model[1], artificial neural network[6-10] and adaptive neural fuzzy[11,12] models for deformation and force prediction.

However, due to the difficulties of testing and complexities of nonlinearity modeling, the characterization of biological cells material properties have not been sufficiently covered. For example, in studying the properties of biological cells using the micropipette aspiration technique, different material parameters have been reported [3, 13-15].

In this research, inverse finite element optimization algorithm have been used to estimate hyperelastic material parameters for computing Young modulus and Poisson's ratio of mouse oocyte cell in cell indentation experiment. By matching the simulated forces to the experimental data, the algorithm iteratively finds the hyperelastic parameters. Finite element simulation has been implemented with Abaqus/Standard 6.9 and it has been coupled with optimization algorithm which has been implemented in Matlab software. Experimental data of mouse oocyte captured from [16] which earlier have been generated by Yu sun and his co-workers [17].

2. MATERIAL MODEL

In virtual reality based medical simulators, haptic rendering is based on linear elastic modeling with small deformation assumptions [18]. Since medical instruments induce large deformations [18], linear elastic models are

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not accurate and cell behavior under large deformations (such as this study) must be described by the nonlinear elasticity theory [18].

On the other hand, for the time-independent experiment (such as underlying cell injection experiment [17]), hyperelastic material model which its parameters can be determined by the strain energy potential function (U) is suitable. For this purpose the neo-Hookean strain energy potential this is widely used in soft tissues and biological cells simulations [3, 18], has been selected to describe the near incompressible hyperelastisity. The form of the three dimensional incompressible neo-Hookean strain energy potential is given by [19]:

$$U = C_{10}(\bar{I}_1 - 3) + \frac{1}{D_1}(J^{el} - 1)^2 \quad (1)$$

where U is the strain energy per unit of the reference volume, C_{10} and D_1 are material parameters; $\bar{I}_1$ and J^{el} ,respectively, are the first deviatoric strain invariant and elastic volume ratio.

3. MODEL PARAMETER ESTIMATION ALGORITHM

In order to enter the complex contact and boundary conditions between the micropipette and cell into the modeling, inverse finite element optimization algorithm has been applied (Figure 1). By fitting the simulated forces from the finite element simulation to the experimental forces; the algorithm iteratively finds the hyperelastic material parameters.

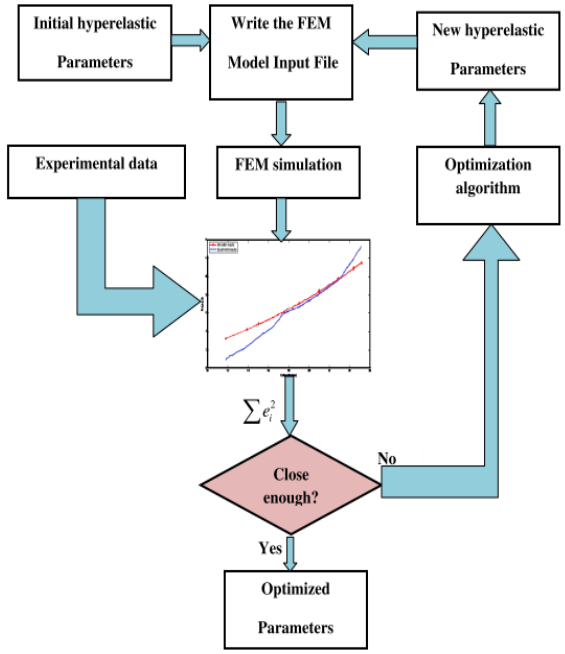

Figure1: Inverse finite element optimization algorithm.

In order to compare the matching of the finite element modeling predictions to the experimental data, the fitness parameter δ is used to measure deviation between the experimental data and the modeling results [2, 4].

$$\delta = \frac{1}{n}\sum_{i=1}^{n}\left[\frac{F_{\exp}(i) - F_{sim}(i)}{F_{\exp}(i)}\right]^2 \quad (2)$$

where $F_{\exp}$, F_{sim} and n ,respectively, are the experimental force, simulated force and total number of data. In order to update the hyperelastic parameters the finite element simulations are automatically iterated using the Levenberg–Marquardt optimization algorithm [20, 21]. In each iteration, the hyperelastic parameters are updates as:

$$P_{i+1} = P_i + inv(H)J^T(F_{\exp}(i) - F_{sim}(i)) \quad (3)$$

Where

$$H = J^T J + \lambda I \quad (4)$$

$$J = \frac{F_{sim}(perturbed) - F_{sim}(i)}{perturbation} \quad (5)$$

In the above relations, P is the estimated hyperelastic parameters matrix and J , H ,respectively, are Jacobean and Hessian matrix. The simulation parameters are included in the algorithm implicitly. For this reason, with varying and perturbing each hyperelastic parameter, running the finite element simulation and then evaluating the effects of perturbation, the Jacobean matrix are numerically computed.

It has been assumed that the cell is a homogenous, isotropic and continuous solid. The finite element model has been built with ABAQUS/CAE 6.9. The inverse finite element optimization algorithm has been implemented in Matlab software (Mathwork, R2008a, USA). After running the first simulation with initial guesses, the Matlab program reads the output Abaqus file and evaluates the next parameters. Then the updated hyperelastic parameters are written into a new input file to utilize by the next simulation of Abaqus program. The optimization algorithm has been coupled with the finite element simulation to repeat the algorithm automatically. After a certain number of iterations if the fitness parameter (δ) reaches a constant value, the algorithm will be finished and, the optimized hyperelastic parameters (C_{10} , D_1) will be determined.

Then, the initial shear modulus, μ_0 , and initial bulk modulus, K_0 , can be determined using the following relations [19]:

$$\mu_0 = 2C_{10} \quad (6)$$

$$K_0 = \frac{2}{D_1} \quad (7)$$

Also, the Poisson's ratio, ν, [19] and Young modulus, E ,[22] are determined as:

$$\nu = \frac{\frac{3k_0}{\mu_0} - 2}{\frac{6k_0}{\mu_0} + 2} \quad (8)$$

$$E = 2\mu_0(1+\nu) \quad (9)$$

4. RESULTS AND DISCUSSIONS

The convergence history of the objective function (δ) using the inverse finite element optimization algorithm which indicating a rapid convergence have been shown in Figure 2.

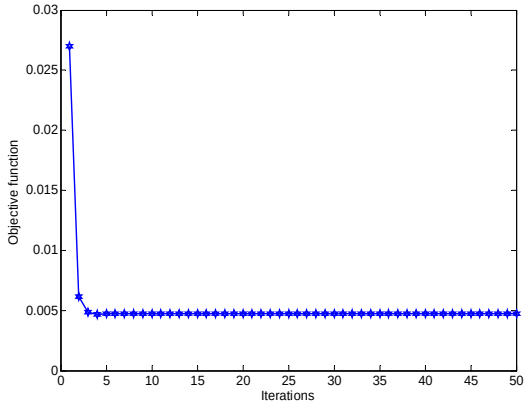

Figure2: Objective function (δ) values versus the number of iterations.

Also, the normalized hyper elastic parameters versus the number of iterations have been shown in Figure 3.

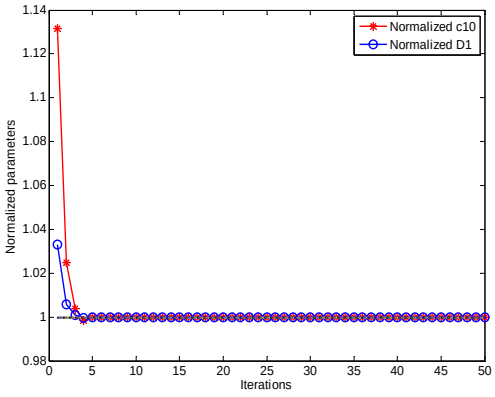

Figure3: convergence history of the normalized hyperelastic parameters.

The values of initial and optimized hyperelastic parameters and fitness function have been presented in Table 1.

TABLE1
THE VALUES OF INITIAL SHEAR MODULUS, BULK MODULUS, POISSON'S RATIO AND YOUNG MODULUS FOR MOUSE OOCYTE CELL.

$\mu_0(MPa)$	$K_0(1/MPa)$	ν	$E(KPa)$
0.0103	187.8095	0.5	30.8

The force-deformation curve of the cell using the optimized hyperelastic parameters in comparison with the experimental observations has been shown in Figure 4.

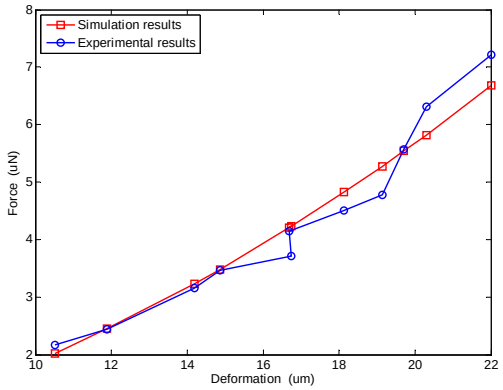

Figure4: comparison of the finite element predicted forces with experimental data versus deformation.

However, a limitation which may happen by the implemented optimization algorithm is that it may give a local minimum. Therefore, by changing the initial guess values, the sensitivity and robustness of the algorithm with respect to these variations have been tested. Results show that the algorithm is unaffected by the rate of the initial guesses when they have been varied (5, 10, 20). The results of sensitivity analysis for six different initial points have been shown in Figure5.

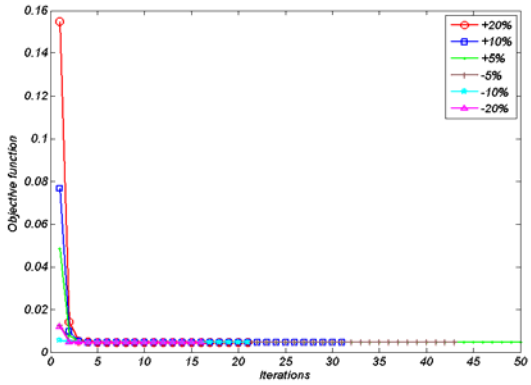

Figure5: Convergence history of the objective function, starting from six different initial guesses.

The initial shear modulus, initial bulk modulus, Poisson's ratio and Young modulus which have been ,respectively, computed using relations 1 to 4 have been presented in Table 2.

TABLE 2
THE INITIAL AND OPTIMIZED NEO-HOOKEAN PARAMETERS AND THE FINAL VALUE OF THE FITNESS FUNCTION.

Initial parameters		Estimated parameters		δ
$C_{10}(MPa)$	$D_1(MPa)$	$C_{10}(MPa)$	$D_1(MPa)$	0.0047
0.0058	0.011	0.0051	0.0106	

From Table 2, it is observed that estimated Poisson's ratio is $\nu = 0.5$. This subject confirms the assumption of in compressibility which has been previously considered in the case of mouse oocyte and other biological cells [2, 17]. Moreover, in previous studies on mouse oocyte cell [2, 17], it has been reported that its membrane Young modulus is 17 kPa which is lower than the Young modulus of the whole cell that has been calculated in this study.

5. CONCLUSION

Here, the procedure of inverse analysis for estimation of hyperelastic parameters through best fit of a cell model to given experimental data, has been described. The algorithm has been applied to a mouse oocyte cell model in cell indentation experiment. It was observed that computed Young modulus of the whole cell is grater that the Young modulus of its bio membrane .Also, the evaluated Poisson's ratio confirms the fact that cell material has an incompressible behavior. Moreover, the sensitivity of the algorithm on six different initial guesses was also tested. Convergence was successfully illustrated in all cases. One application of the model is that it can be implemented to the virtual reality based simulations to estimate virtual forces or deformations in real time.

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