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Determination of the mechanical and physical properties of cartilage by coupling poroelastic-based finite element models of indentation with artificial neural networks

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ABSTRACT

One of the most widely used techniques to determine the mechanical properties of cartilage is based on indentation tests and interpretation of the obtained force–time or displacement-time data. In the current computational approaches, one needs to simulate the indentation test with finite element models and use an optimization algorithm to estimate the mechanical properties of cartilage. The modeling procedure is cumbersome, and the simulations need to be repeated for every new experiment. For the first time, we propose a method for fast and accurate estimation of the mechanical and physical properties of cartilage as a poroelastic material with the aid of artificial neural networks. In our study, we used finite element models to simulate the indentation for poroelastic materials with wide combinations of mechanical and physical properties. The obtained force–time curves are then divided into three parts: the first two parts of the data is used for training and validation of an artificial neural network, while the third part is used for testing the trained network. The trained neural network receives the force–time curves as the input and provides the properties of cartilage as the output. We observed that the trained network could accurately predict the properties of cartilage within the range of properties for which it was trained. The mechanical and physical properties of cartilage could therefore be estimated very fast, since no additional finite element modeling is required once the neural network is trained. The robustness of the trained artificial neural network in determining the properties of cartilage based on noisy force–time data was assessed by introducing noise to the simulated force–time data. We found that the training procedure could be optimized so as to maximize the robustness of the neural network against noisy force–time data.

1. Introduction

Osteoarthritis (OA) is a common chronic disease that develops as a result of the degeneration of articular cartilage (AC) which frequently leads to pain and limited mobility (Liu et al., 2014; Lories and Luyten, 2012). In AC, collagen type II fibers mainly provide tensile mechanical properties while negatively charged proteoglycans macromolecules (PGs) provide shear and compressive mechanical properties of AC (Sophia Fox et al., 2009). Changes in the mechanical and physical properties of AC such as Young's modulus and permeability as a result of PG loss and collagen fibril disintegration are the hallmarks of disease progression. Mechanical characterization of AC and its changes over time is therefore an important research line within the OA community (Stolz et al., 2009; Wang et al., 2006; Wilusz et al., 2013). Available tools to investigate the mechanical behavior of cartilage are compression tests among which the most important ones are confined compression (Boschetti et al., 2004; DiSilvestro and Suh, 2001; Wilson et al., 2005), unconfined compression (Lu and Mow, 2008; Mow et al., 1980; Wilson et al., 2005), and indentation tests (Korhonen et al., 2002; Pawaskar et al., 2010; Warner et al., 2001).

The indentation test offers the advantage of obtaining local mechanical properties of cartilage accurately (Rettler et al., 2013). It also does not require cartilage tissue to be cut loose from the bone, and consequently sophisticated processes for preparing cartilage before the test do not cause damage to the tissue. It is therefore

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possible to state that the indentation test is an absolutely non-destructive test (Franz et al., 2001; Lu and Mow, 2008) and consequently it can be performed *in vivo* (Knecht et al., 2006; Sim et al., 2014). Indentation tests are shown to be capable of identifying OA and healthy cartilage at nano-scale (Stolz et al., 2009) and determining the fixed charge density of cartilage tissue (Le and Fleming, 2008).

One way to specify cartilage's mechanical properties is to apply analytical solution to the data from the indentation test. Since no analytical solution for the indentation of poroelastic materials exists, this approach may lead to errors for the prediction of mechanical properties of cartilage (Oyen, 2011; Rauker et al., 2014). The other approach is to use finite element method combined with optimization algorithm by which cartilage properties can be derived (Cao et al., 2006; Wang et al., 2006). This however requires cumbersome iterative processes until the best finite element model for the problem is achieved (Gupta et al., 2009; Miller and Morgan, 2010; Richard et al., 2013; Seifzadeh et al., 2012). Moreover, the entire modeling process needs to be repeated for every new indentation test.

In this study, we first used finite element models (FEM) to simulate the indentation of cartilage as a poroelastic material in relaxation mode for a wide range of properties and their combinations i.e. Young's modulus, Poisson's ratio, permeability, and friction coefficient between the indenter and cartilage surface. Thereafter, we used force–time data obtained from FEM as inputs and properties of articular cartilage as targets to train an artificial neural network (ANN). This enabled us to extract the precise properties of articular cartilage under similar boundary conditions as were used in FEM. This approach will potentially pave the way toward predicting accurate properties of healthy and OA articular cartilage when the experimental data from indentation tests are accessible. The long-term aim of the current study is to conceive a method by which a user-friendly environment becomes available that could be used to distinguish between healthy and diseased tissue.

2. Methodology

2.1. Finite element modeling

We used a finite element modeling platform i.e. Abaqus 6.11 to simulate the indentation test of a cartilage specimen introduced as a poroelastic material. The essential equations required for modeling cartilage are presented (Manda, 2010; Mow et al., 1980) (Appendix A). Mechanical and physical properties as well as model assumptions were chosen based on the previous work (Pawaskar et al., 2010; Spilker et al., 1992; Warner et al., 2001). The cartilage specimen was assumed to have a thickness of 3 mm and an axisymmetric radius of 20 mm to maximally eliminate the edge effects on the fluid velocity vectors. A spherical indenter with the radius of 5 mm was used in the model (Fig. 1). The cartilage properties are provided in Table 1 (Goldsmith et al., 1995; Pawaskar et al., 2010; Spilker et al., 1992; Warner, 2000). The details of finite element modeling as well as the required boundary conditions are presented in Appendix B.

We developed an Abaqus user subroutine to identify the contact between the cartilage and the indenter based on Pawaskar's work (Pawaskar et al., 2010). In this method, when contact stress on the cartilage's surface is greater than a threshold value, fluid flow is forced to stop. The developed user subroutine processed the information received from the solver in each iteration and created a common block that included all nodes with contact stress greater than the threshold (URDFILL). The common block could be accessed by another subroutine (FLOW). In the FLOW, the closest integration point to the node that has a contact stress greater than the threshold value is selected and fluid flow is stopped by setting both the seepage coefficient and sink pore pressure to zero. Otherwise, it continues to use a seepage coefficient equal to one while the sink pore pressure remains zero.

2.2. Artificial neural networks (ANNs) application

In this section, we describe how we trained an ANN in MATLAB 2013 for predicting the cartilage mechanical and physical properties such as elastic modulus, Poisson's ratio, permeability, and friction coefficient using force–time data (Appendix C. How does artificial neural network function?).

The indentation test was simulated for a wide range of different mechanical and physical properties according to the previously used data from human articular cartilage (Pawaskar et al., 2010): elastic modulus between 0.1 and 1 MPa, Poisson's ratio between 0.01 and 0.2, permeability between $10^{-3}$and 10^{-2} mm^4/N s, and friction coefficient between 0 and 0.05. For every property, the variation interval was divided into 10 and finite element models were run for all possible combinations resulting in 10,000 simulations. The output of this parametric study was force–time data with 121 different time points which are originated from Abaqus resampling procedure. The input matrix for training the ANN therefore contained $10{,}000 \times 121$ force–time data and the target matrix contained $10{,}000 \times 4$ cartilage properties. In the current sturdy we used a number of 30 hidden neurons for the noise-free data and 40 hidden neurons for noisy data. Following the training of the network, the curves by which the mechanical and physical properties can be determined were introduced into MATLAB and the results were effortlessly achieved (CPU time of 0.11 s using a computer (3.33 GHz (2 cores)).

Table 1
Properties of articular cartilage used in finite element simulations (Goldsmith et al., 1995; Pawaskar et al., 2010; Spilker et al., 1992; Warner, 2000).

Parameter	Value
Poisson's ratio, v	0.08
Permeability, k	4.0×10^{-3} mm^4/N s
Initial void ratio, e_0	4.0 (80% interstitial fluid)
Coefficient of friction, f_f	0.02
Seepage coefficient, k_s	1 mm^3/N s – Flow 0 mm^3/N s – No flow
Young's modulus, E	0.54 MPa

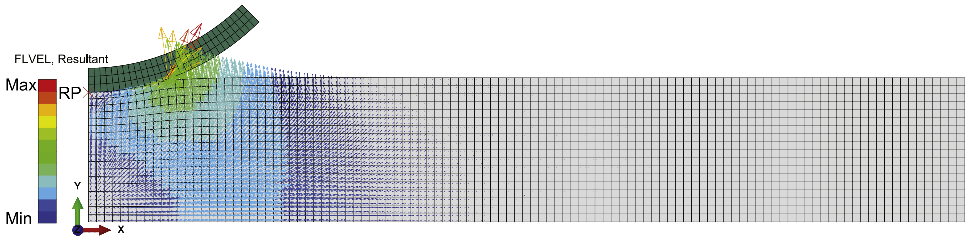

Fig. 1. The axisymmetric model used for simulation of indentation experiments. Fluid velocity vectors are depicted in this figure for demonstration purposes.