

Concentration-Specific Constitutive Modeling of Gelatin Based on Artificial Neural Networks

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Gelatin phantoms are frequently used in the development of surgical devices and medical imaging techniques. They exhibit mechanical properties similar to soft biological tissues [1] but can be handled at a much lower cost. Moreover, they enable a better reproducibility of experiments. Accurate constitutive models for gelatin are therefore of great interest for biomedical engineering. In particular it is important to capture the dependence of mechanical properties of gelatin on its concentration. Herein we propose a simple machine learning approach to this end. It uses artificial neural networks (ANN) for learning from indentation data the relation between the concentration of ballistic gelatin and the resulting mechanical properties.

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1 Introduction

One of the most popular methods to identify material parameters is to compare experimental results with computer simulations of the same set-up and to adjust the material parameters in the simulations iteratively until the difference between experiments and simulations becomes minimal [2]. This method has, however, also some well-known disadvantages [2, 3]. To overcome these disadvantages, alternative approaches have been proposed. For example, [4] suggested using ANN for constructing inverse functions mapping measurement data such as the force-depth curves of spherical indentations directly onto material parameters. Here we extend this idea so that it will allow us to predict the mechanical properties of gelatin from its concentration even if no experimental data are available for the specific gelatin of interest.

2 Methods

We conducted spherical indentation experiments at an indentation velocity of $0.01 \text{ mm}^{-1}\text{s}$ with gelatin cylinders of varying gelatin mass concentrations $\alpha \in \{5, 6, 7.5, 10, 12.5, 15, 17.5, 20 \text{ \%}\}$, Figure 1a. The measurements for the 6 % gelatin where withheld for validation. The proposed approach is based on two ANN [5] implemented using the software library

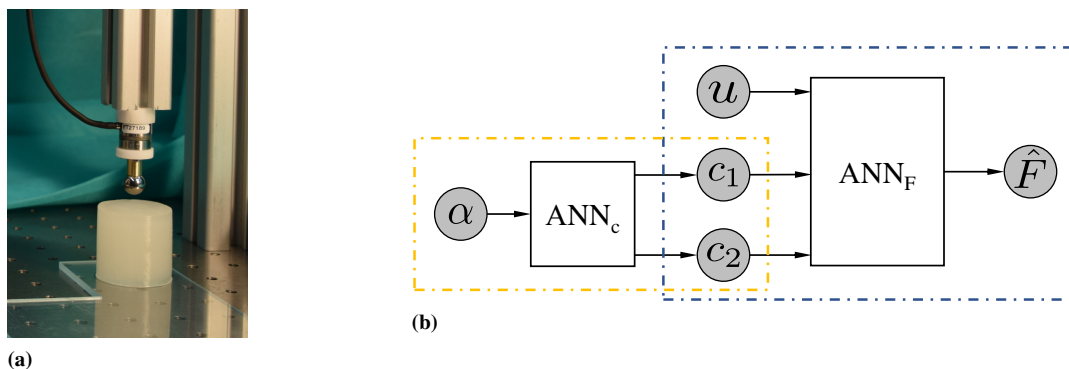


Fig. 1: (a) Experimental setup of the displacement-driven spherical indentation. (b) Schematic representation of our machine learning architectures: the network ANN_c maps the gelatin concentration α to its material parameters c_1 and c_2 . The second network ANN_F maps the material parameters and a given indentation depth u on the indentation force \hat{F} .

TensorFlow [6]. Our machine learning architecture is illustrated in Figure 1b. In this architecture, the first network ANN_F is trained with data from finite element simulations of the fictitious indentation experiments. For these simulations we simulated the gelatin as a hyperelastic, incompressible Mooney-Rivlin material with strain energy $\Psi = c_1(I - 3) + c_2(II - 3)$, with

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I and II the first two invariants of the right Cauchy-Green tensor \mathbf{C} . Previous to each simulation the material parameters c_1 and c_2 are randomly drawn from a range representative of the mechanical properties of typical ballistic gelatin. Thus, every simulation yields a force-depth curve along with the related material parameters as training data for ANN_F . After training, this network is able to predict from a given indentation depth and Mooney-Rivlin material parameters the associated indentation force. The training of the network ANN_F can be performed without any experimental data.

The second network ANN_c maps gelatin concentrations on the associated material parameters. It is trained with experimental force-depth curves of gelatin with varying concentrations α while keeping the weights of ANN_c constant. For the training of both ANN, the sum of squared differences between the predicted indentation force and the correct one (known from simulation or experiment) is minimized.

3 Results

After training is completed, the combination of ANN_c and ANN_F cannot only resemble the constitutive behavior of the gelatin samples provided for training. In addition, it can also predict the material properties of gelatin with a mass concentration different from any represented in the experimental training data, and it can predict for such gelatin also the whole force-depth curve to be expected during an indentation experiment. These results are illustrated in Figure 2. Note, that the 6 % concentration, highlighted in red in Figure 2, was withheld for validation of our trained ANN.

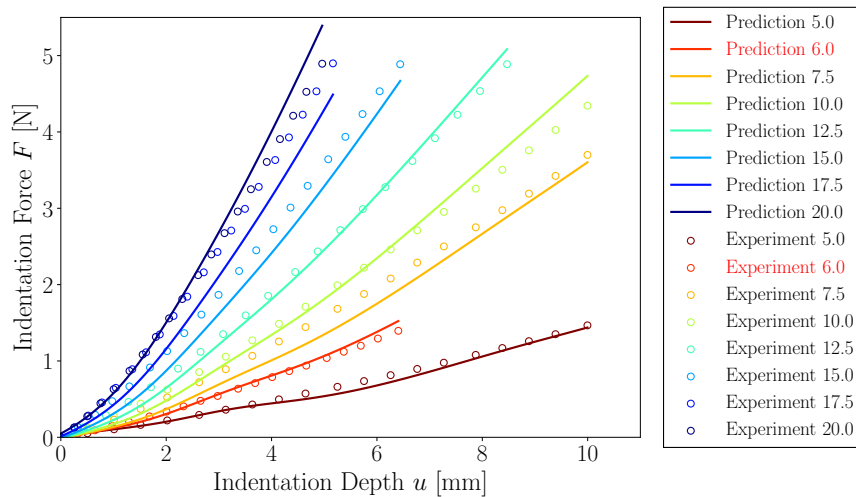


Fig. 2: Comparison of predicted and experimentally obtained force-depth curves for all considered gelatin mass concentrations. All but the 6 % concentration, which is highlighted in the legend in red, have been used to train ANN_c .

4 Conclusions and Discussion

The present work demonstrates how a combination of machine learning and computational mechanics renders it possible to predict concentration-specific material parameters of gelatin. In this contribution the gelatin was assumed to behave hyperelastically. An extension to the more realistic assumption of viscoelastic material behavior will be addressed in future work.

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