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Identification of the concentration-dependent viscoelastic constitutive parameters of gelatin by combining computational mechanics and machine learning

Kian P. Abdolazizi[1,*], **Kevin Linka**[1], **Johanna Sprenger**[2], **Maximilian Neidhardt**[2], **Alexander Schlaefer**[2], and **Christian J. Cyron**[1,3]

[1] Institute for Continuum and Material Mechanics, Hamburg University of Technology, Eißendorfer Straße 42, 21073 Hamburg, Germany.
[2] Institute of Medical Technology and Intelligent Systems, Hamburg University of Technology, Am Schwarzenberg-Campus 3, 21073 Hamburg, Germany.
[3] Institute of Material Systems Modeling, Helmholtz-Zentrum Hereon, Max-Planck-Straße 1, 21502 Geesthacht, Germany.

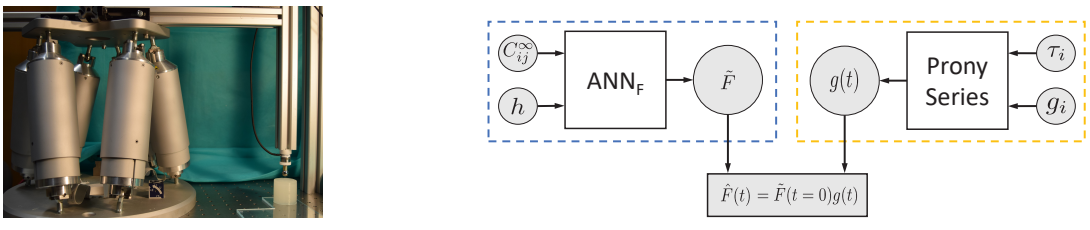
Since the mechanical properties of gelatin are similar to those of soft biological tissues, gelatin is a commonly used surrogate for real tissues, for example in safety engineering or medical engineering. Additional advantages of gelatin over real tissues are lower costs and better reproducibility of experiments. Therefore, constitutive models of gelatin are of great interest. In particular, it is important to capture the concentration dependence of the mechanical properties since the gelatin mass concentration significantly affects the constitutive behavior. To this end, we propose a hybrid approach linking artificial neural networks (ANN) and classical constitutive modeling to relate the gelatin's concentration to its viscoelastic material properties using indentation data.

1 Introduction

Classical methods for identifying material parameters often rely on experiments with homogeneous stress states such as uniaxial tension. Due to its softness, these tests are not feasible for gelatin. Instead, compression or indentation tests with multi-axial stress states are used. The finite element model updating method (FEMU) is one of the most popular methods to identify material parameters from multi-axial tests. In the FEMU experimental results are compared with computer simulations of the same set-up and the material parameters in the simulations are iteratively adjusted to minimize the deviation of the simulation from the experiment [1]. Disadvantages of the FEMU are its computational cost and noise sensitivity if only scant data is available [1,2]. In contrast, [3] used an ANN as an inverse function to map force-depth data of indentation experiments directly onto the unknown mechanical properties. Based on this idea, we developed a simple model that infers the viscoelastic properties of gelatin solely from its mass concentration, which positively correlates with its stiffness.

2 Methods

Spherical indentation experiments were performed at different indentation velocities $v \in \{0.01, 0.1, 1.0 \text{ mm s}^{-1}\}$ with gelatin cylinders of varying gelatin mass concentrations $\alpha \in \{5, 6, 7.5, 10, 12.5, 15, 17.5, 20\ \%\}$, Fig. 1a. The measurements for the $10\ \%$ gelatin were withheld for validation. Each measurement was repeated four times.



(a) **(b)**

Fig. 1: **(a)** Experimental setup of spherical indentation using a hexapod robot. **(b)** Surrogate model: artificial neural network ANN$_F$ maps material parameter C^{∞} and a given indentation depth h on the indentation force $\tilde{F}$. A Prony series expansion represents the time-dependent relaxation modulus g of the gelatin. Each Prony term i is defined by a pair of material parameters g_i and τ_i.

We replicated the indentation tests with a finite element (FE) model, where gelatin was modeled as a hyperelastic, incompressible Neo-Hookean material with strain energy function $\Psi = C^{\infty}(\mathrm{I}_1 - 3)$, wherein I_1 is the first invariant of the right Cauchy-Green tensor $\mathbf{C}$ and C^{∞} is a material parameter. Using this setup, indentation tests were simulated and for

* Corresponding author: e-mail kian.abdolazizi@tuhh.de, phone +49 40 42878 2562

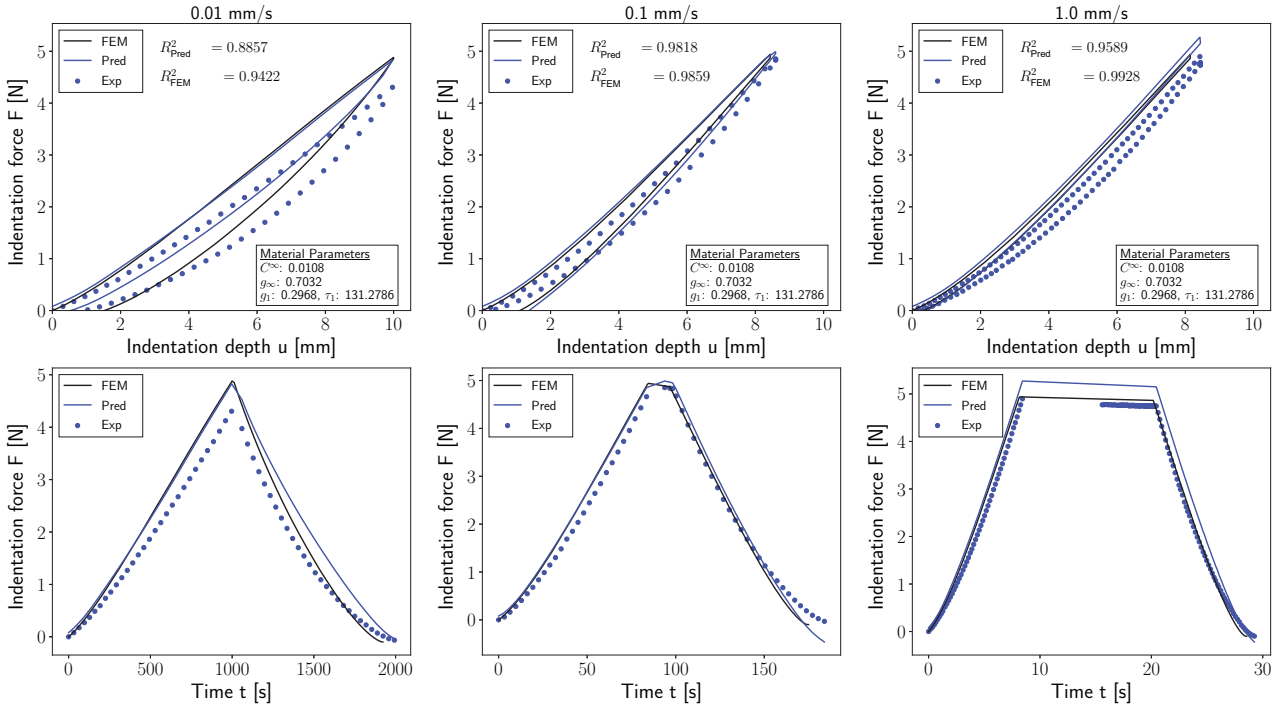


Fig. 2: Force-depth (top) and force-time (bottom) curves of the unknown 10 %-gelatin for different indentation velocities. Surrogate model (Pred) and FE model (FEM) are compared to experimental measurements (Exp). $R^2_{\text{Pred}} \approx 1$ and $R^2_{\text{FEM}} \approx 1$ indicate a good prediction of the model and FE simulations.

each simulation C^∞ was drawn at random from a uniform distribution within an interval representative for the mechanical properties of gelatin. From each simulation one obtains a force-depth curve along with the corresponding material parameter C^∞. The results of the FE simulations were used to train a neural network ANN_F (Fig. 1b) to map an indentation depth h and a material parameter C^∞. to an associated indentation force $\tilde{F}$. Viscoelastic relaxation was accounted for by a Prony series $g(t) = g_\infty + \sum_{i=1}^{N} g_i \ \exp(-\frac{t}{\tau_i})$ implemented in a recursive formula [4]. Combining this Prony series multiplicatively with the output of ANN_F provided a surrogate model of the indentation force in the form $\hat{F}(t) = \tilde{F}(t=0)g(t)$. Using this fast surrogate model, the material parameters $\{C^\infty, g_\infty, g_i, \tau_i\}$ could efficiently be determined for each concentration by choosing them such that they minimized the mean square error between the output of the surrogate model and the experimentally measured time-dependent indentation force.

3 Results

After having determined the viscoelastic properties of gelatin for a large range of concentrations by inverse analysis using our surrogate model, we sought to predict the viscoelastic properties for an unknown gelatin concentration by combining curve fitting with our surrogate model. Indeed this way we could predict the force-depth (and -time) curve with a high accuracy (coefficient of determination $R^2_{\text{Pred}} \approx 1$) as shown in Fig. 2. To further verify the predicted material parameters, we used them also in FE simulations of the indentation experiment. The results are given in Fig. 2. The simulations closely match the experiments, i.e. $R^2_{\text{FEM}} \approx 1$. Altogether, we demonstrated how combining machine learning and classical constitutive modeling allows predicting concentration-specific, viscoelastic material parameters of gelatin. An ANN was trained with FE simulations and subsequently used as basis for a computationally efficient surrogate model, which could be used in an inverse analysis instead of the material parameters instead of computationally much more expensive FEMU iterations.

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