PARAMETER FITTING FOR A VISCOELASTIC CONSTITUTIVE MODEL USING A MACHINE LEARNING MODEL

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Introduction

The characterization of biological tissues by means of constitutive models is a necessary task to carry out realistic and reliable finite element simulations.

The arteries, in particular, present different mechanical properties, such as hyperelasticity and viscoelasticity, which are fundamental for their correct biological functioning. Although it is possible to describe these properties through constitutive models, this task involves the calibration of material parameters of such models in order to properly mimic the mechanical behavior of the studied material.

To determine these constants, optimization techniques that iteratively account for results computed via finite elements are often used, thus resulting in a very slow computational process. Therefore, it is proposed in this work to accelerate the process by creating a metamodel through a neural network trained with synthetic data obtained from finite element simulations. Adjustments of this type have been made with purely hyperelastic constitutive models [1], but have not yet been included. In this investigation, the non-linear viscoelastic component is included using a constitutive model recently proposed by Latorre et al. [2].

Method

A uniaxial relaxation test in the circumferential direction of a one-year-old guinea pig aorta artery is used to study the viscous effect described in these experimental results. To characterize the constitutive model, a fully connected neural network is trained, with 3 hidden layers formed by 6 neurons, using data from 5000 finite element simulations, changing only the parameters of the viscoelastic constitutive model and maintaining the hyperelastic parameters previously adjusted in a work already published by the authors [3]. The input of the network are 6 parameters that correspond to the viscous parameters of the viscoelastic constitutive model, while the corresponding output is made up of the data produced by the reduction of the dimensionality applied to 4001 time points by each simulation performed. This reduction of the dimensionality is done through the use of Principal Component Analysis (PCA) [4]. Therefore, with this network a metamodel is obtained, which receive the viscous parameters and deliver data that represent the applied stresses.

Based on this metamodel, an optimizer is applied to determine the viscous parameters that deliver the best fit to the experimentally measured stress. With this last step, it is possible to adjust the parameters of the viscoelastic constitutive model that describe the data obtained from the uniaxial relaxation test of an artery.

Result

A metamodel with a Mean Squared Error (MSE) of 2.46% is obtained, which affects the accuracy of the parameters obtained after applying the optimizer. However, a set of parameters similar to that delivered by the classical method [3] is achieved. After plotting the curve delivered by the metamodel with the parameters obtained in [3] and contrasting it with the experimental data, some differences are observed in the beginning of the relaxation process (Figure 1) that are also attributed to the error of the metamodel. On the other hand, the time to obtain the optimal parameters is much lower compared to the methods that iterate with finite element simulations.

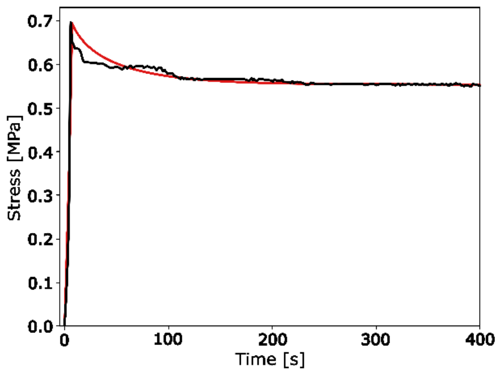

Figure 1: Comparison of the experimental response (black) and that of the metamodel (red) after evaluating the optimal viscous parameters obtained in [3].

References

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