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Estimation of in vivo constitutive parameters of the aortic wall using a machine learning approach. (English) Zbl 1440.74229

Comput. Methods Appl. Mech. Eng. 347, 201-217 (2019).

Summary: The patient-specific biomechanical analysis of the aorta requires the quantification of the *in vivo* mechanical properties of individual patients. Current inverse approaches have attempted to estimate the nonlinear, anisotropic material parameters from *in vivo* image data using certain optimization schemes. However, since such inverse methods are dependent on iterative nonlinear optimization, these methods are highly computation-intensive. A potential paradigm-changing solution to the bottleneck associated with patient-specific computational modeling is to incorporate machine learning (ML) algorithms to expedite the procedure of *in vivo* material parameter identification. In this paper, we developed an ML-based approach to estimate the material parameters from three-dimensional aorta geometries obtained at two different blood pressure (i.e., systolic and diastolic) levels. The nonlinear relationship between the two loaded shapes and the constitutive parameters is established by an ML-model, which was trained and tested using finite element (FE) simulation datasets. Cross-validations were used to adjust the ML-model structure on a training/validation dataset. The accuracy of the ML-model was examined using a testing dataset.

MSC:

74L15 Biomechanical solid mechanics
65D17 Computer-aided design (modeling of curves and surfaces)
76Z05 Physiological flows
74S99 Numerical and other methods in solid mechanics

Keywords:

machine learning; neural network; constitutive parameter estimation

Software:

Adam; DeepFace; GNMT; LIBSVM

Full Text: DOI

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