Liu, Zeliang; Wu, C. T.; Koishi, M.

A deep material network for multiscale topology learning and accelerated nonlinear modeling of heterogeneous materials. (English) Zbl 1440.74340

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Summary: In this paper, a new data-driven multiscale material modeling method, which we refer to as deep material network, is developed based on mechanistic homogenization theory of representative volume element (RVE) and advanced machine learning techniques. We propose to use a collection of connected mechanistic building blocks with analytical homogenization solutions to describe complex overall material responses which avoids the loss of essential physics in generic neural network. This concept is demonstrated for 2-dimensional RVE problems and network depth up to 7. Based on linear elastic RVE data from offline direct numerical simulations, the material network can be effectively trained using stochastic gradient descent with backpropagation algorithm, further enhanced by model compression methods. Importantly, the trained network is valid for any local material laws without the need for additional calibration or micromechanics assumption. Its extrapolations to unknown material and loading spaces for a wide range of problems are validated through numerical experiments, including linear elasticity with high contrast of phase properties, nonlinear history-dependent plasticity and finite-strain hyperelasticity under large deformations. By discovering a proper topological representation of RVE with fewer degrees of freedom, this intelligent material model is believed to open new possibilities of high-fidelity efficient concurrent simulations for a large-scale heterogeneous structure. It also provides a mechanistic understanding of structure – property relations across material length scales and enables the development of parameterized microstructural database for material design and manufacturing.

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material network; building blocks; machine learning; nonlinear plasticity; large deformations

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