ABSTRACT

Deep Learning-based Material Representation and Noniterative Multiscale Topology Optimization

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For decades, topology optimization method has been actively researched and applied in various disciplines. In addition to applications in macroscopic structure design, topology optimization has been applied in material design to derive optimal microstructures. Material design via homogenization-based topology optimization has created a new design possibility for metamaterials, such as negative Poisson's ratio. Subsequently, research has been conducted for simultaneous optimization of both macro- and microscopic structures, termed as multiscale topology optimization (MSTO), which offers the advantages of lightweight, robust, and multifunctional design. In particular, MSTO requires at least two or more variables for each material point, whereas single-scale topology optimization (SSTO) involves only a single variable. However, the increasing number of variables and homogenization equations increases the computational demand. Therefore, this thesis aims to reduce such computation burden in MSTO using emerging deep learning approaches. This study proposes a deep-learning approach for MSTO and an experimental MSTO acceleration method.Intro

First, a deep-learning-based MSTO method (DL-MSTO) is proposed with a material representation scheme using a generative adversarial network (GAN) and a vision

transformer (ViT)-based predictor. A generator network learns the lower-dimensional representation of the microstructural manifold and provides microstructural images from the low-dimensional latent vectors. Thereafter, a ViT-based predictor is trained to predict the corresponding homogenized elasticity matrix. More specifically, the predictor network is modified based on a technique inspired by Cholesky decomposition to ensure the positive semi-definiteness. The generator and predictor networks are integrated into the MSTO process to reduce the number of variables and replace homogenization computation.

The proposed DL-MSTO method enables a DL-based accelerating approach for the MSTO. Accordingly, a noniterative MSTO prediction method is further introduced based on implicit neural representation and graph neural networks (GNNs). A multilayer perceptron (MLP) behaves as an implicit function that maps from the spatial coordinates to the latent vector field for a given MSTO problem. In this thesis, we selected a graph to represent an MSTO problem defined in an irregular design domain. As a GNN encodes the MSTO problem into the parameters defining the MLP, the GNN-based encoder is trained to determine the optimal MLP approximator. The trained encoder and approximator predict the (near-)optimal latent vector field over the design domain without iteration.

Comprehensively, the qualitative and quantitative evaluation using the isotropy-dominated and anisotropic microstructures datasets demonstrated the validity of the generator and predictor networks. The effectiveness and efficiency of the method were verified by comparing the benchmarks of the conventional MSTO and the proposed DL-MSTO. Furthermore, the noniterative MSTO prediction method was validated using the training dataset consisting of randomly sampled MSTO problems. Conclusively, the MSTO solution inferred from the proposed noniterative MSTO method can aid an engineer to obtain intuitive multiscale designs without solving the MSTO problem.