ICCES, 2023, vol.27, no.3

Tech Science Press

DOI: 10.32604/icces.2023.09091

PROCEEDINGS

A Machine Learning Framework for Isogeometric Topology Optimization

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ABSTRACT

Topology optimization (TO) is an important and powerful tool to obtain efficient and lightweight structures in conceptional design stage and a series of representative methods are implemented [1-5]. TO are mainly based on the classical finite element analysis (FEA), resulting in an inconsistency between geometric model and analytical model. Besides, there are some drawbacks of low analysis accuracy, poor continuity between adjacent elements, and high computational cost for high-order meshes. Thus, isogeometric analysis (IGA) is proposed [6] to replace FEA in TO. Using the Non-Uniform Rational B-Splines (NURBS), IGA successfully eliminates the defects of the conventional FEA and forms a new research direction, isogeometric topology optimization (ITO) [7-12]. Although these methods have high accuracy and high solution efficiency, they are accompanied with significant time costs. With the rapid development of machine learning (ML) and deep learning (DL), data-driven TO methods are generated to reduce computational costs and speed up optimization process [13-18]. In this paper, an ITO method based on deep neural networks is proposed. The computational time of optimization can be effectively reduced while ensuring high accuracy. With an IGA-FEA two-resolution SIMP method, the ML dataset can be obtained during early iterations of the topology optimization process. Thus, there is no need to pre-process in the whole framework. Unlike existing data-driven methods, generating datasets online both significantly saves data collection time and enhances relevance to the design problem. In the optimization process, the ML model can be updated online by continuously collecting new data to ensure that the optimized topology structures are closer to the standard results. Through a series of 2D and 3D design examples, the generality and reliability of the method are effectively demonstrated by the relative differences and speedups and its time-saving advantage becomes more obvious as the design scale increases. Furthermore, the impacts of framework parameters and neural network hyper-parameters on the results are studied through several controlled experiments.

KEYWORDS

Isogeometric analysis; topology optimization; machine learning; solid isotropic material with penalization

Funding Statement: The work was supported by the National Natural Science Foundation of China (52005192), the Fundamental Research Funds for the Central Universities (HUST:2020kfyXJJS016), the Project of Ministry of Industry and Information Technology (TC210804R-3) and the National Key R&D Program of China (2020YFB1708300).

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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