Real-Time Topology Optimization Based on Convolutional Neural Network by Using Retrain Skill

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Abstract

To realize a real-time structural Topology Optimization (TO) efficiently, it is important to make sufficient use of the information during the TO process. A step-by-step training method is proposed to improve the deep learning model prediction accuracy based on the topology optimization method of Solid Isotropic Material with Penalization (SIMP). By making use of the "depth" of one sample data, the training method can effectively improve the deep learning model prediction accuracy without increasing the sample set size. The step-by-step training method is the combination of several independent deep learning models (sub-models). The sub-models have familiar model structures, and they can be trained in parallelization. During the Deep Learning (DL) model training process, these features reduce the difficulties in adjusting sub-models' parameters and the sub-model training time cost. Meanwhile, this method is achieved by the local end-to-end training process. During the DL model predicting process, the increase of total prediction time cost can be ignored. The trained deep learning models can predict the optimized structures in real-time. Several numerical examples of dynamic optimization problems are used to verify the effectiveness of the proposed training method. The method proposed in this study provides a novel implementation technology for the real-time TO of structures.

Key words: *Topology Optimization; Real-Time Topology Optimization; Convolutional Neural Network; Deep Learning*

1. Introduction

Topology Optimization (TO) is used to find the material distribution in the structural design domain to obtain optimized structural performances[1]. Numerous TO methods have been proposed, such as the Solid Isotropic Material with Penalization (SIMP) method[2], evolution structure optimization method[3], and moving morphable component method[4]. These methods have been predominately employed in multidisciplinary structural optimization problems[5]. Nevertheless, they usually require a large amount of repeated iterations of finite element analysis, hence the computational cost increases rapidly with an increased number of elements and problem dimensions.

Deep Learning (DL) methods have been rapidly developed in recent years. During the training process, the DL model establishes a functional relationship between the input and output data. A well-trained DL model can provide optimized results with less computational overhead than the traditional TO methods and meet the requirements of real-time TO at the same time.

This study proposes a step-by-step training method for the combination of the SIMP TO method and DL. By using this approach, the prediction accuracy of the DL model can be greatly improved compared to the traditional end-to-end training method. The problem description section describes relevant training methods based on offline and online DL models. Then in the numerical results section, several frequency optimization examples are used to verify the effectiveness of the proposed training method. Finally, a summary of this study is provided in the conclusion section.

2. Problem description

A number of investigations have been performed on applying DL to the TO method. For instance, Gorkem[6] used two DL models with different loss functions to accelerate the TO process, alleviating the problem of structural discontinuity prediction. Yu[7] used a Convolution Neural Network (CNN) and condition Generative Adversarial Network to convert the low-resolution TO result to high-resolution TO result. These two approaches are based on the offline training method, which allows well-trained models to obtain optimized results in real-time. The improvement of model prediction accuracy is usually achieved by changing loss function[6], sample set size[8], and model structures[9]. However, there is a lack of consideration for the validity of input data, and the intermediate process information of TO is rarely used.

On the other hand, several online training methods have been assessed for the TO. Unlike its offline counterparts, online training methods directly integrate the DL model into the TO process to accelerate the whole calculation process. Chi[10] accelerated the TO process by using stage sensitivity as the training labels. Guo[11] replaced the calculation process of microstructure stiffness in traditional multi-scale optimization with the DL model to improve the optimization efficiency. Although the online training method is not dependent on the scale of sample set, information from the TO process has to be consecutive input, which limits the improvement of real-time TO efficiency.

To solve the aforementioned problems of the offline and online methods, a step-by-step training method that discretizes the optimization process is proposed. By extracting the information of key steps during the TO process, this method is able to improve prediction accuracy without increasing the sample set size. The fundamental eigenfrequency optimization problem is used to validate the proposed method.

3. Numerical results

To assess the performance of the proposed step-by-step training model, an academic structural model is employed and discretized by 221×31 finite elements. The constraint and loading condition of the structure is shown in Fig 1. The middle elements on the left and right boundary are fixed, and lumped masses are randomly placed in load domain (81×31). There are total 2511 samples, with 150 of them for validation.

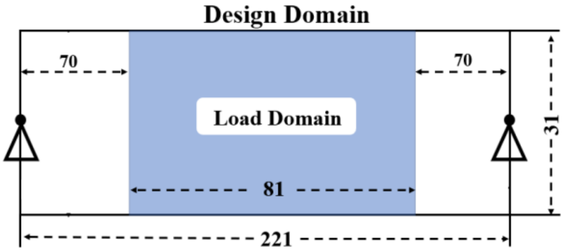

Fig.1 Schematic of structural constraint and loading condition.

Table 1 presents five training results (differentiated by the random lumped mass distribution) of Model-1 and Model-2 based on the traditional end-to-end training method[6-8] and the step-by-step training method proposed in this study, respectively. The optimization results by the SIMP TO method are also listed in Table 1 for reference. The "Obj" column shows the fundamental eigenfrequency value for each structure. Expect for the training method, all other factors including sample set size and the structure of the DL model are kept the same.

Comparing the prediction results of Model-1 and Model-2, it can be found that the Model-2 results have clearer structure boundaries and higher similarity with the SIMP optimization results. Comparison of the "Obj" values (such as row 1 in table1) suggests the "Obj" value of Model-2 is closer to the SIMP optimization result. Model-2 decreases the relative error of "Obj" from 6.05% (Model-1) to 1.76%, indicating the step-by-step training method can effectively improve the prediction accuracy of the DL model without increasing the sample set size. In addition, the proposed training method reduces the number of intermediate density elements (i.e., element with density between 0.4 to 0.6), which affects the clarity of the DL prediction results, by 36.76% compared to the traditional method in the first example of Table 1 (row 1). By leveraging the information during the TO process, the training method proposed in this study can effectively reduce the intermediate density elements in the predicted results.

Table 1 Comparison of the optimized structure between traditional offline training model, step-by-step training model and optimized results by SIMP.

Model-1 Results		**Model-2 Results**		**Results based on SIMP**	
Predicted Structures	Obj	Predicted Structures	Obj	Optimized structures	Obj
	34.66		36.24		36.89
	35.42		36.69		36.50
	31.23		36.72		36.75
	36.63		37.10		36.33
	35.17		36.09		35.07

4. Conclusion

In this study, a novel step-by-step DL training method is proposed for real-time SIMP TO of structures. By scattering the TO process, information can be gathered from key steps to aid optimization. This training method can effectively improve the accuracy of model prediction without increasing the sample set size and alleviate the gray element problem in model prediction results.

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