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A Deep Convolutional Neural Network Approach as Surrogate Model for Topology Optimization

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It is widely recognized that traditional topology optimization (TO) method can be time consuming, mainly due to the finite element analysis (FEA) embedded in the iteration. In the past few years, the rise of deep learning (DL) has been driving the researchers to adopt artifical neural network (ANN) as a surrogate model to accelerate TO [1-3]. However, most research focus on treating the whole TO process as a black box, taking its inputs (boundary conditions, volume fraction, etc.) and outputs (the optimized structure) to train the surrogate model. This paper propose another angle to approach the problem, which is to focus mainly on the most time-consuming FEA part in the TO process. There are a number of surrogate models existing for structural FEA [4]. In this paper, an encoder-decoder convolutional neural network (CNN) is trained using data generated from the FEA module in the 88-line matlab code implementing the classic solid isotropic material with penalization (SIMP) method [5]. The trained network takes the boundary conditions and element densities as inputs and output the compliance of each element. Then, the compliance information is fed into the traditional TO numerical optimizer to derive the final optimized structure.

The main advantages of the proposed method are listed as follows.
1) The numerical optimizer is kept in the TO process. Therefore, the structural disconnection reported in other research [1,2] is naturally avoided.
2) By performing downsampling and upsampling in the CNN, the proposed method has a certain degree of generalization ability.
3) Future research may grow on the idea of seperating the two components of TO. For example, training another surrogate model for the numerical optimizer, and combining it with the FEA surrogate model to achieve further acceleration.

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