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Investigation into the topology optimization for conductive heat transfer based on deep learning approach

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ABSTRACT

A deep learning approach combining with the traditional solid isotropic material with penalization (SIMP) method is presented in this paper to accelerate the topology optimization of the conductive heat transfer. This deep learning predictor is structured based on the deep fully convolutional neural network. The validity and accuracy of this deep learning approach is investigated based on the typical 'Volume-Point' heat conduction problems. The time consumption of the optimization process will be reduced significantly by introducing the deep learning approach.

1. Introduction

Increasingly integrated and miniaturized electronic devices require more efficient ways of extracting internal heat out of the system. A valid approach named as conductive heat transfer by introducing a limited amount of conduit materials with high thermal conductivity is spreading utilized [1, 2], especially when the electronics to be cooled has a low thermal conductivity and its volume is restricted. The high thermal conductivity materials form the cooling path for aiding to heat transfer to the environment or heat sink [3]. To augment and improve the thermal performance, several methods have been developed to design and optimize the distribution and layout of a limited amount of high conductive material, such as the constructal theory [4], the variable thickness method [5], the evolutionary structural optimization (ESO) method [6], the level set method [7], the bionic method [8], and so on.

The solid isotropic material with penalization (SIMP) method is another simple and efficient approach, which is widely introduced to the topology optimization of conductive heat transfer [9–12]. For the layout design of the restricted conduit materials with high thermal conductivity k_h in the basic materials with low thermal conductivity k_0, the design goal is to obtain the optimal distribution of these two different thermal conductivities in the design domain. The optimizing problem becomes have only one variable, that is the effective thermal conductivity, based on the SIMP method by introducing a design parameter δ. Thus, the effective thermal conductivity k throughout the whole design domain is redefined as.

$$k = k_0 + \delta^p(k_h - k_0), \delta \in [0,1]$$

Where $\delta = 0$ represents the basic material $(k = k_0)$; $\delta = 1$ corresponds to the conduit material $(k = k_h)$; $0 < \delta < 1$ represents a composite material consisting of basic material and conduit material. For encouraging the optimization algorithm to favour design variables of either $\delta = 0$ or $\delta = 1$ and reducing the amount of composite material, a penalization factor p is introduced $(p > 1)$.

For the topology optimization of a typical 'Volume-Point' heat conduction problem (seeing Fig. 1), the change process of material layout from iteration to iteration based on the SIMP method is presented in Fig. 2. It is very clear that the first stage of topology optimization for conductive heat transfer based on the SIMP method is the general redistribution of the materials, and the layout of the materials varies tremendously iteration by iteration as shown from Fig. 2(a) to (d). The second stage is converging and correcting the material layout to the final results. At this process, the silhouette as well as the global layout structure of the materials keeps unchanged and only the local structure will be corrected to the final converging result as shown from Fig. 2(e) to (h). Based on this characteristic, the second stage of topology optimization could be seen and treated as a process of the image segmentation and recognition.

Deep learning with the intrinsic superiorities of high efficiency and accuracy is widely approached in many fields including the image segmentation and recognition [13–17]. In this paper, an application of deep learning on the topology optimization for conductive heat transfer is investigated by introducing a deep learning method into the second stage of topology optimization based on the SIMP method.

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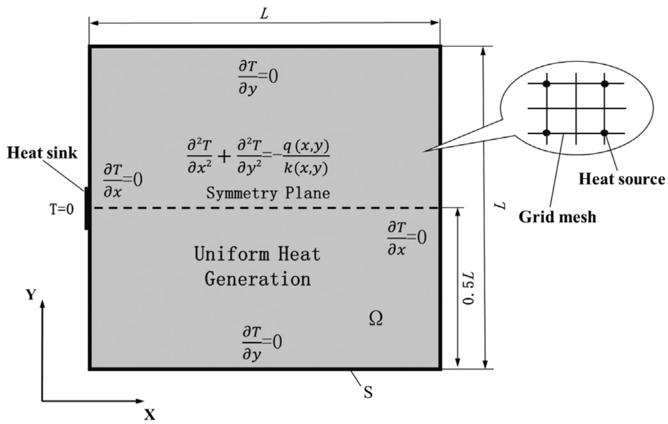

Fig. 1. The model of the typical 'Volume-Point' heat conduction problem.

2. Methodology and model

In current work, the topology optimization of conductive heat transfer is based on the distribution of the high thermal conductive materials with a restricted volume fraction within a design domain. Considering the steady state heat conduction, the temperature field of conductive heat transfer in a two-dimensional design domain Ω is governed as follows:

$$\frac{\partial}{\partial x}\left(k\frac{\partial T}{\partial x}\right)+\frac{\partial}{\partial y}\left(k\frac{\partial T}{\partial y}\right)=-Q$$

where k and T denote the effective thermal conductivity and the temperature distribution influenced by the parameter δ^p based on SIMP method, Q represents the heat generating rate within the heat source.

For the boundary S of the design domain Ω, two boundary conditions are introduced as

$$\mathrm{T}|_{\mathrm{S}_1}=\mathrm{T}_0$$

$$\mathrm{k_n}\frac{\partial T}{\partial n}\bigg|_{\mathrm{S}_2}=0$$

where $\mathrm{S}=\mathrm{S}_1\cup\mathrm{S}_2$. S_1 represents the boundary of the heat sink, whose temperature is set as a fixed value of T_0, and $T_0=0$ in current work. The heat flux along the outward normal vector in the boundary S_2 is equal to 0, which denotes the adiabatic boundary condition.

By applying the finite element method to solve the temperature field, the governing equation will be rewritten as

$$\boldsymbol{KT}=\boldsymbol{F}$$

where $\boldsymbol{K}$, $\boldsymbol{T}$ and $\boldsymbol{F}$ represent the global conductivity matrix, the nodal temperature vector and the nodal load vector, respectively.

The volume of the design domain Ω is V_0. The volume fraction of the high thermal conductive material is restricted to $\phi_{\max}$. The optimization problem of the layout for the materials with high thermal conductivity can be formulated as.

Find:

$$\delta=\{{}^1\delta_e,{}^2\delta_e,\cdots,{}^N\delta_e\}^{\mathrm{T}}$$

Minimize:

$$C=\boldsymbol{T}^{\mathrm{T}}\boldsymbol{KT}=\sum_{i=1}^{N}({}^i\delta_e^{\,p}\cdot T_e^{\mathrm{T}}\cdot K_e\cdot T_e)$$

Subject to:

$$\boldsymbol{KT}=\boldsymbol{F}$$

$$\sum_{i=1}^{N}({}^i\delta_e\cdot{}^iv_e)\le\phi_{\max}\cdot V_0$$

$$0\le{}^i\delta_e\le1$$

where N is the total number of the discrete element, v denotes the volume, and the subscript e represents that it is the variable size in the element. Thus, ${}^i\delta_e$ denotes the design parameter of the element i.

The optimization problem is solved using the optimality criteria method (OCM) presented in [18]. The convergence criterion is that the difference ε in the design parameter δ between the two iterations before and after is less than 0.01. Due to the intrinsic checkerboard problem of the SIMP method, in order to obtain the final layout without any composite material, that is the value of design parameter δ must be 0 or 1, a filtering technique named as 'Image Binarization' is applied onto the result of the converging iteration, and the threshold is selected by the golden section method. For the optimization of the 'Volume-Point' problem as shown in Fig. 1, the final layout of the material with high thermal conductivity before and after filtering processing is presented in Fig. 3(a) and (b). The volume fraction of the materials with high thermal conductivity is restricted to 30% in current case, $\phi_{\max}=0.3$. Throughout this paper, the heat sources are evenly distributed inside the design domain (as shown in Fig. 1), and their heat generating rate is equal to 1.

3. Deep learning and training

According to the characteristic of the optimization process of the conductive heat transfer based on the SIMP method, an initial iterating is conducted using the SIMP method, and then its result is input into a deep learning predictor. After the training and learning by the deep learning predictor, a predicted layout of the materials with high thermal conductivity will be output as the final result of the topology optimization. The deep learning predictor is based on a deep fully convolutional neural network in current work, consists of an encoder and a decoder and its architecture is similar with the U-Net system presented in [19]. The architecture of the deep learning predictor in current work is presented in Fig. 4.

The encoder of this deep learning predictor consists of eight convolutional layers, as illustrated in Table 1 and Fig. 4. This encoder could be divided into four levels, and each level contains two convolutional layers. The kernel size of every convolutional layer is 3 × 3. Each convolutional layer in the level 1 contains eight feature maps. The number of the feature map for each convolutional layer in level 2, level 3 and level 4 is 16, 32 and 64, respectively. The activation function of the convolutional layer is ReLU function. For the first six convolutional layers, a Max pooling layer is inserted after every two convolutional layers, and its kernel size is 2 × 2. The function of the Max pooling is reducing the number of parameters and guaranteeing the translation invariance of inputs. To improve the learning capacity and avoid over-fitting during the training process, a Dropout layer is inserted as the regularization between the third and fourth convolutional layers in current work. The decoder of this deep learning predictor reverses the construction of the encoder as presented in Table 1, so it also consists of eight convolutional layers. However, the Max pooling layers are replaced with the Up sampling layers, and every Up sampling layer is followed by a concatenation. Followed the decoder, a fully convolutional layer is introduced as the output layer, whose kernel size is 1 × 1, and its activation function is Sigmoid function. The input of the deep learning predictor in current work is two figures obtained from the topology optimization based on the SIMP method: one is the distribution of the design parameter δ, and the other is the difference of the design parameter between the two iterations before and after, that is the gradient distribution of the design parameter δ.

A pseudo-random sample problem of conductive heat transfer is design to generate the training dataset for deep learning. The grid number is 80 × 80 in current work. In order to improve the universality of the algorithm and prevent the over-fitting phenomenon during training, the volume fraction of the high thermal conductive material