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Topology optimization of acoustic-structural systems based on deep transfer learning framework for enhancing sound quality

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Abstract

Sound quality is an important measure of the sound performance of acoustic devices. However, multi-frequency calculations in sound quality optimization can lead to poor solvability of the optimization problem. Data-driven approach is an effective way to solve multi-frequency computing problems. However, as the acoustic device products are updated, the structure or environment will change. The original neural network model will no longer be applicable and the prediction accuracy will be severely reduced. The new optimization task requires the collection of new data samples and the training of new neural networks. The extensive data collection process and iterative optimization process further reduce the solvability of the sound quality optimization problem. For the sound quality optimization of acoustic devices, this paper proposes a data-driven acoustic-structural topology optimization design method that can quickly and accurately predict the acoustic frequency response and significantly improve the computational efficiency problem. Deep transfer learning is also introduced to achieve fast and accurate prediction of acoustic frequency response using a small amount of sample data in a new structure/environment. The main contributions of this paper are as follows: (1) A new agent model based on deep neural network (DNN) is proposed to replace the complex finite element model, combined with Movable Morphable Components (MMC) method with a small number of design variables to achieve sound quality optimization of acoustic devices. (2) Deep transfer learning is introduced for the DNN training, which realizes the rapid and accurate prediction of sound pressure frequency response in new tasks by using a small amount of sample data, and enhances the adaptability of DNN agent model in different

optimization tasks. (3) Numerical examples demonstrate that the proposed method can reduce the data dependence. In the multi-layer iterative optimization task, using small sample data for multiple transfer learning can achieve efficient optimization design and greatly reduce the design complexity.

Keywords: topology optimization, acoustic-structural system, artificial neural network, transfer learning, MMC, sound quality

1 Introduction

In recent decades, acoustic performance of electronic devices has become a hot research topic. Sound quality, defined as the smooth output of sound with a sufficiently large sound pressure level (SPL) amplitude in the interested frequency band, is a very important acoustic indicator for electronic devices such as mobile phones and loudspeakers. When it comes to the design of the sound quality of products, researchers are often faced with the problems caused by multi-frequency calculations. In addition, different design solutions often require the same computational challenges. The repetitive and tedious analysis and calculation process greatly affects the production and updating of products. Therefore, the need for fast and accurate real-time analysis and calculation results has become urgent for rapid innovation of electronic devices.

With the expansion of the application of topology optimization in various industries, the problem of acoustic topology optimization design is gradually gaining widespread attention. Related studies on acoustic optimization can read in [1-5]. However, there are relatively few relevant studies dealing with multi-frequency computational problems in acoustic topology optimization work. In fact, it is generally necessary to consider the acoustic performance over a wide range of frequency bands when dealing with sound quality problems. Because of the frequency dependence, finite element models require the acoustic response to be calculated at each frequency. This results in time-consuming frequency sweeps. Worse still, the need for finite element calculations at each iteration step in the optimization problem adds to the tediousness of the calculations. An effective approach is to discretise the wider frequency band into a number of frequency points and perform finite element calculations. However, the cost of this approach is a loss of accuracy in the sound curve.

The introduction of machine learning has become a proven solution to the above problem. In the field of topological optimization, relevant optimization techniques combined with machine learning have been gradually applied to different problems. Chandrasekhar et al. [6] considered a simple compliance minimization problem and achieved an optimized distribution of multiple materials under a total mass-constraint by means of an artificial neural network. White et al. [7] used neural network for multiscale topology optimization, where a gradient-based nonlinear topological optimization method is adopted for macroscopic optimization, while the elastic response of microscale metamaterial is calculated by neural network agent model instead of finite element model. Abueidda et al. [8] predicted the optimized structure of topology optimization design problem with material and geometric nonlinearities by using a convolutional neural network model. Lei et al. [9] used machine learning technique for real-time structural topology optimization in an explicit framework based on Movable Morphable Components (MMC).

Machine learning can effectively solve the problem of multi-frequency computation in acoustic problems. However, in the design process, different structural design schemes need to be verified and compared. Although the structure is only slightly changed, the neural network used in the original scheme may not be suitable for the data of new structure, and the predictive performance may be significantly reduced. To obtain accurate acoustic response of each structure, the time-consuming data collection process and neural network training process need to be re-performed.

The goal of transfer learning is to use a small amount of data to learn relevant knowledge from the source task to help the target task create a high-performance model. Some research has been carried out in related fields. In order to cope with complex aerospace design tasks, Min et al. [10] studied transfer learning, multi-task learning technology and multi-view learning technology in data-driven agent model. Zhang et al. [11] proposed a hierarchical adaptive prediction method based on deep transfer learning to predict the remaining service life of bearings in the multi-stage degradation process. Aiming at the optimization task of heat source layout with different boundary conditions, Zhao et al. [12] introduced deep transfer learning to quickly predict temperature field layout.

In this paper, a new agent model based on deep learning and deep transfer learning is developed for the sound quality optimization problem, which enables fast and accurate prediction of optimized acoustic structures for different optimization tasks using small sample data. The main contributions of this paper are as follows:

1) A new deep learning-based agent model is proposed to replace the complex finite element model in multi-frequency acoustic optimization calculations to achieve fast and accurate prediction of the optimized structure for sound quality problems.

2) DNN training introduces deep transfer learning, which increases the adaptability of the DNN agent model in different situations by exploiting information between different sound quality optimization tasks.

3) Some numerical arithmetic examples demonstrate that the proposed method can reduce data dependence and achieve fast optimized design of the final task through multiple sample transfer learning in a multi-layer optimization task.

The rest of the paper is organised as follows. Section 2 introduces the mathematical model of sound quality optimization and some details of deep learning method. Section 3 gives some numerical examples to verify the effectiveness of the proposed method. Finally, some conclusions are drawn in section 4.

2 Methods

2.1 Optimization problem

In this work, the goal of sound quality optimization is to maximize the SPL amplitude in the interested frequency band and improve the uniformity of the SPL frequency response by changing the topology of the acoustic design domain. The general approach is to find the optimized structure in the design domain that provides the best transmission channel for the sound waves to achieve a certain acoustic performance (as shown in Figure 1).

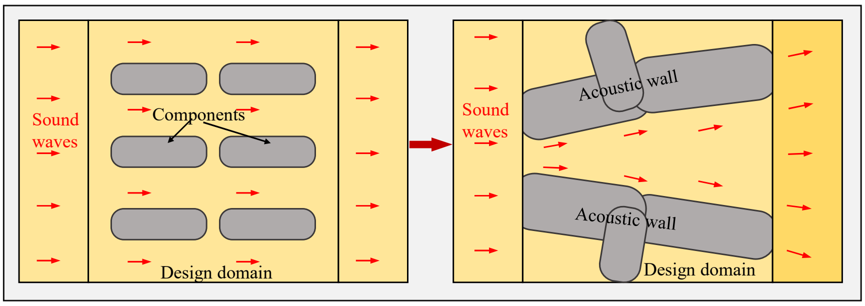

Figure 1: The basic idea of acoustic topology optimization problem.

Under the MMC method [13], the optimization problem can be formulated as follows:

$$\begin{aligned} &\text{find: } \boldsymbol{d} = (\boldsymbol{d}_1^\top, \dots, \boldsymbol{d}_N^\top)^\top, \\ &\text{min: } \quad I = I(\boldsymbol{d}), \\ &\text{s.t. } \mathbf{K}(\boldsymbol{d})\boldsymbol{U} = \boldsymbol{F}, \\ &V(\boldsymbol{d}) \leq \gamma D_a, \\ &\boldsymbol{d} \subset \mathcal{U}_{\boldsymbol{d}}, \\ &\boldsymbol{U} = \overline{\boldsymbol{U}}, \text{on } \Gamma_{\boldsymbol{U}}, \end{aligned} \tag{1}$$

where $\boldsymbol{d}_i, i = 1, \dots, N$ represents the design variable vector of the i-th component and N is the total number of the components; $\mathcal{U}_{\boldsymbol{d}}$ is the admissible set allowed that $\boldsymbol{d}$ belongs to. The symbol $\mathbf{K}$ is the global stiffness matrix of the acoustic–mechanical problem; $\boldsymbol{U}$ is the structural response that includes mechanical and acoustic fields, respectively; $\boldsymbol{F}$ is the load vector. $V(\boldsymbol{d})$ is the volume occupied by the components, D_a is the given design domain and γ is the volume fraction between 0 and 1.

In this paper, the objective function I of the SPL maximization problem can be expressed as

$$I_1 = -\|p_i\|_2, \qquad \forall i \in [f_l, f_u], \tag{2}$$

where p_i represents the frequency response obtained at frequency i dropping in the frequency band $[f_l, f_u]$. While in the sound quality optimization problem, the SPL response in the whole frequency band should be considered. Thus, the corresponding objective functional is written as

$$I_2 = \eta \left\| I_1^i, I_1^{max} \right\|_2 - I_1^{max}, \qquad \forall i \in [f_l, f_u], \tag{3}$$

where η is a coefficient to control the magnitude of the uniformity of the frequency response in the band. I_1^{max} can be expressed as

$$I_1^{max} = \left(\sum_{i=f_l}^{f_u} \left(I_1^i\right)^p\right)^{\frac{1}{p}}, \tag{4}$$

where p is a penalty factor. In this work, $p = 6$.

2.2 DNN for the prediction of sound pressure

The sound quality optimization needs to solve the sound pressure of each frequency through the calculation of sweep frequency, which is a huge computational process. Therefore, it is difficult to use traditional numerical method directly in the optimization process. In this paper, an agent model based on DNN and deep transfer learning is proposed for rapid and accurate prediction of sound pressure in different optimization tasks.

A typical deep neural network is divided into three layers: the input layer, the hidden layer and the output layer. In this paper, the design variables in MMC method and the frequency are used as the input layer, the sound pressure is used as the output layer. Through training, the DNN can quickly and accurately predict the output corresponding to a series of inputs. However, the prediction performance of the DNN decreases when there are some small changes in boundary conditions such as dimensions of the structure or design domain locations. In order to avoid re-collecting data to train a new DNN, this work introduces a deep transfer learning model to learn the knowledge of the original neural network with a small amount of sample data in order to enable the new DNN to be applied to new tasks. The basic idea is shown in Figure 2.

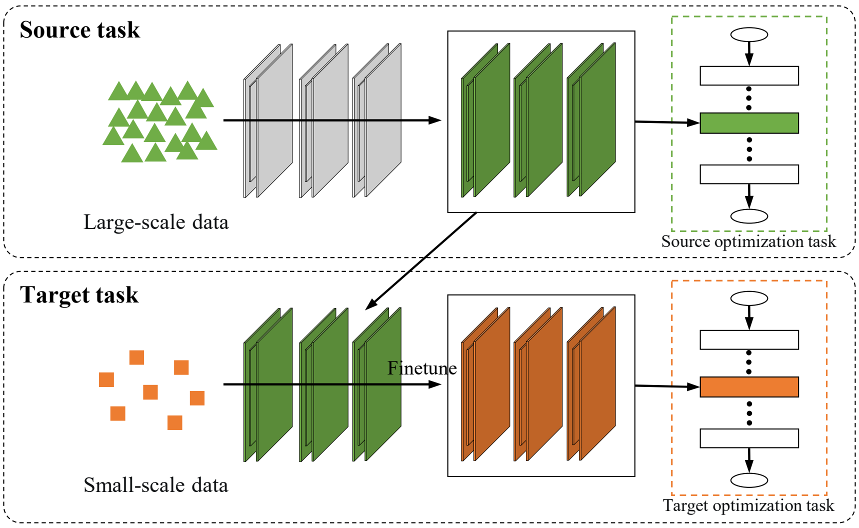

Figure 2: The basic idea of optimization task based on deep learning and deep transfer learning.

3 Results

3.1 Finite element model

In order to verify the feasibility of the proposed method in acoustic optimization problems, the two-dimensional (2D) model shown in Figure 3 is chosen as the finite element model for the optimization problem. The left side of the model is the structural domain with plastic as the material and the right side is the acoustic domain with air as the acoustic medium. Sizes of structure and boundary conditions are shown in Figure 3. The reference point A is located at the centre of the right boundary of the acoustic domain. In this paper, the model dimension for the SPL maximization problem is millimetre, while the sound quality optimization problem is centimetre.

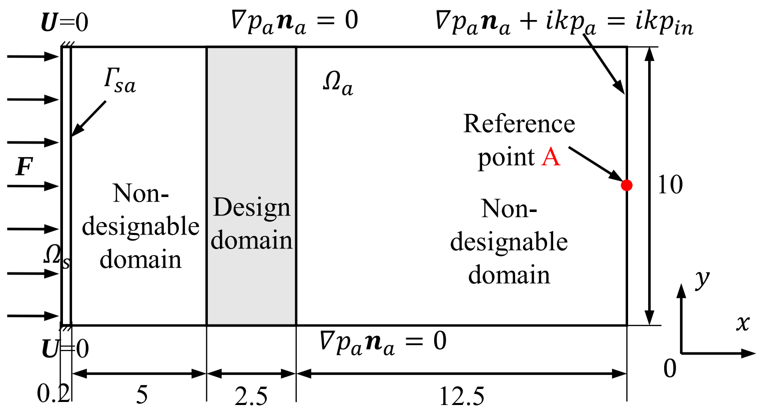

Figure 3: A simple 2D acoustic structure.

3.2 Numerical examples

For the SPL maximization problem, the selected optimization frequency is 7000Hz. To obtain the DNN, 200,000 sets of data were used for training and 40,000 sets for testing. Figure 4(a) shows the initial distribution of the components (material is aluminium) and the optimized predicted structure. The relative error between the predicted value and the real value is less than 2.5%. Figure 4(b) shows the distribution of the SPL field for the original design and the optimized structure. Figure 4(c) shows the SPL curves in 6000-10000Hz of the point A. It can be noted that the SPL increases from 102.73dB to 106.50dB. Time to optimize 200 iteration steps using DNN is 230 seconds (while time to optimize 500 iteration steps using FEM is 1128 seconds).

As shown in Figure 5, the three boundary conditions of the 2D model is slightly modified, and the DNN was gradually fine-tuned with 4000 sets of data at a time. Figure 6(a) shows the optimized structure by the new DNN predictions after transfer learning. Figure 6(b) shows the distribution of the SPL field for the original design and the optimized structure after fine-tuning. Figure 6(c) shows the new SPL curves of the point A. It can be seen that the SPL has increased from 101.77dB to 104.99dB. The time used to collect small sample data and fine-tune the DNN for three times is about 6.5 hours, while the time required to re-collect 240,000 sets of data and train the DNN is over 36 hours. The efficiency of the calculation has been greatly improved.

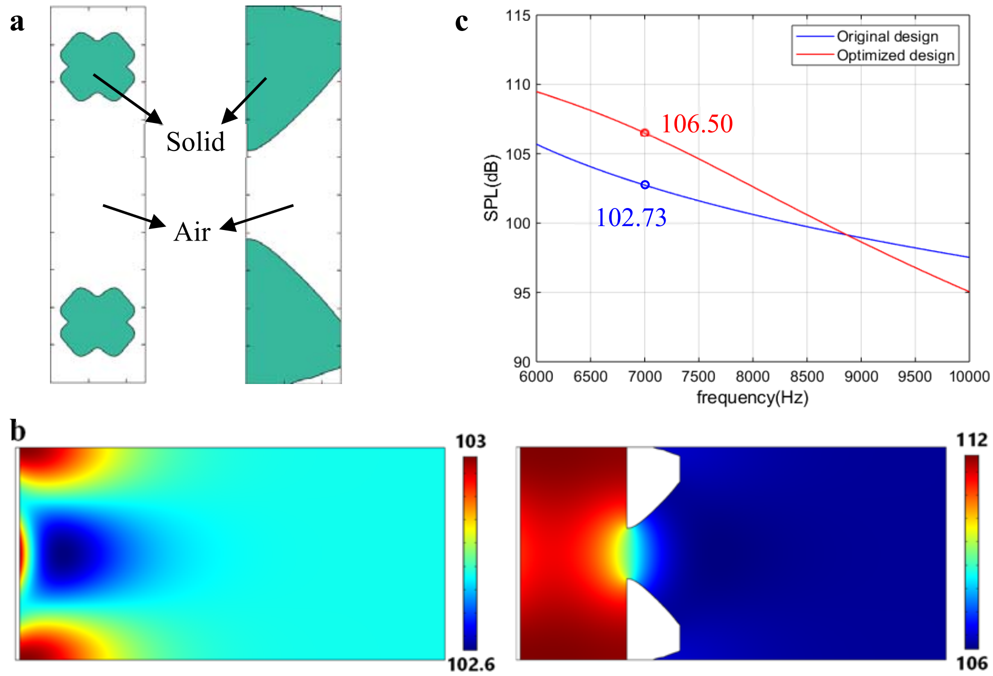

Figure 4: (a) The initial distribution of the components and the optimized structure; (b) Distribution of SPL (dB) of the 2D acoustic structure at f=7000Hz: original design (left) and optimized design (right); (c) SPL curves of the 2D acoustic structure ([6000Hz, 10000Hz]).

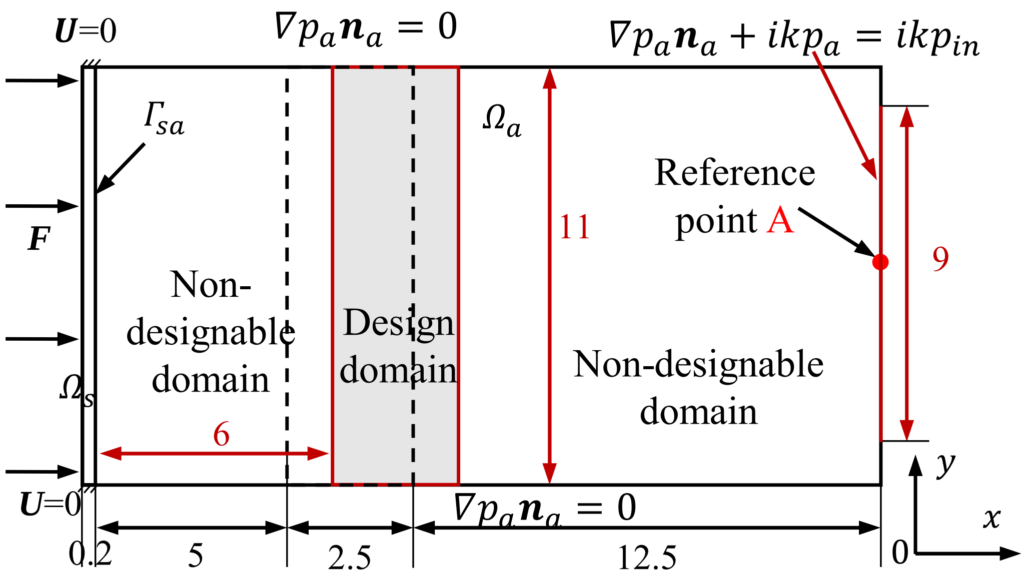

Figure 5: The adjusted two-dimensional acoustic structure.

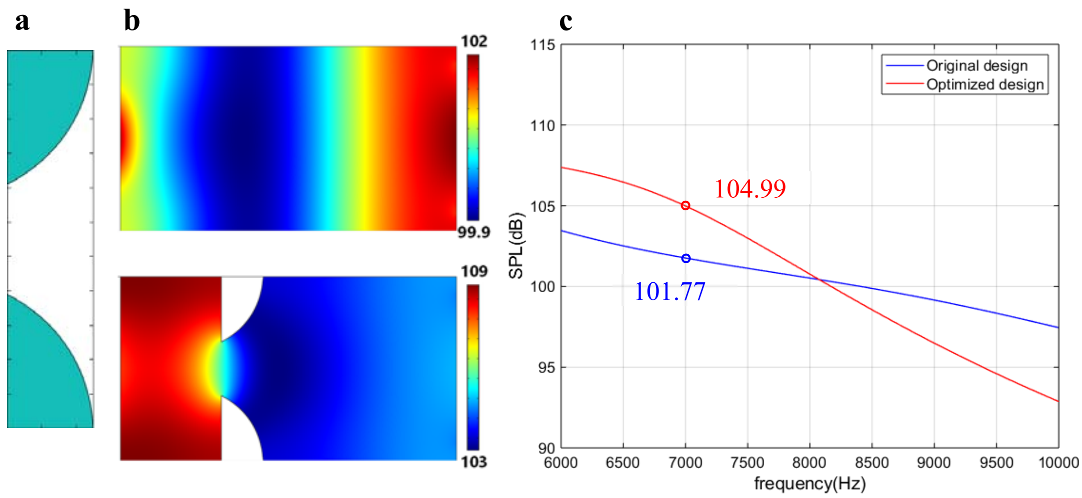

Figure 6: (a) The optimized structure; (b) Distribution of SPL (dB) of the 2D acoustic structure at f=7000Hz: original design (up) and optimized design (down); (c) SPL curves of the 2D acoustic structure ([6000Hz, 10000Hz])

For the sound quality optimization problem, the model still uses the 2D structure shown in Figure 3 and the selected frequency band is 3300-3700Hz. To obtain the DNN, 150,000 sets of data were used for training and 30,000 sets for testing. The coefficient η is 0.01. Figure 7(a) shows the initial distribution of the components and the optimized predicted structure. Figure 7(b) shows the SPL curves in 3300-3700Hz of the point A. It can be noted that the optimized SPL curve is noticeably smoother and the sound quality has been greatly improved. In this example, the time consumed for sound quality optimization (200 iteration steps) with 41 frequency points is 310 seconds (the time using the FEM method with 5 frequency points is 1110 seconds).

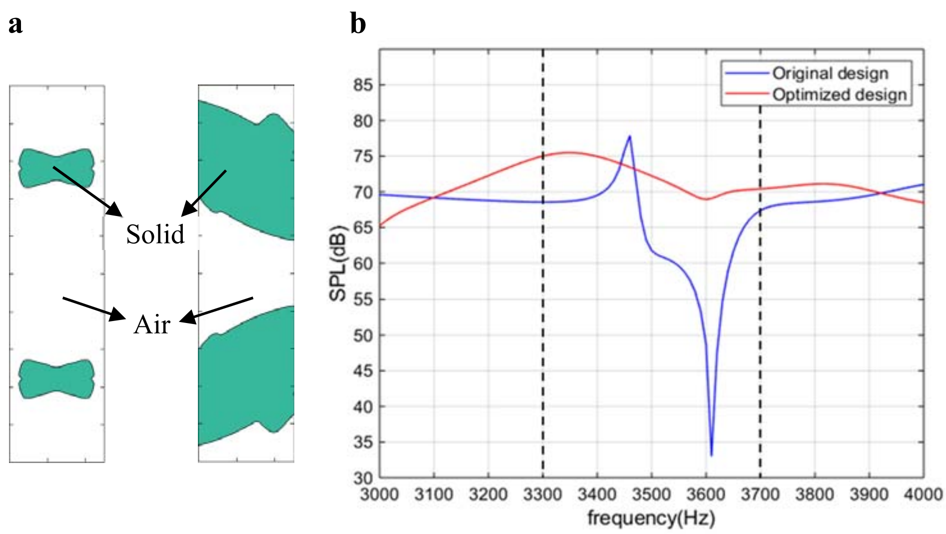

Figure 7: (a) The initial distribution of the components and the optimized structure; (b) SPL curves of the original structure and the optimized structure ([3000Hz, 4000Hz])

As shown in Figure 8, only the location of the design domain is fine-tuned and 4000 data is used to learn the knowledge of the original DNN. The coefficient η is 0.001. Figure 8 shows the optimized predicted structure. Figure 8 shows the SPL curves in 3300-3700Hz of the point A. It can be noted that the SPL curve becomes very smooth, and the optimized structure can still be predicted by using the new DNN to obtain the best sound quality after the design domain location is slightly adjusted. In sound quality problem, due to the randomness of the frequency, the stiffness matrix of each set of data needs to be recalculated, data collection is an extremely time-consuming (over 14 days) effort. Therefore, it is very advantageous to use transfer learning with small sample data based on the source DNN.

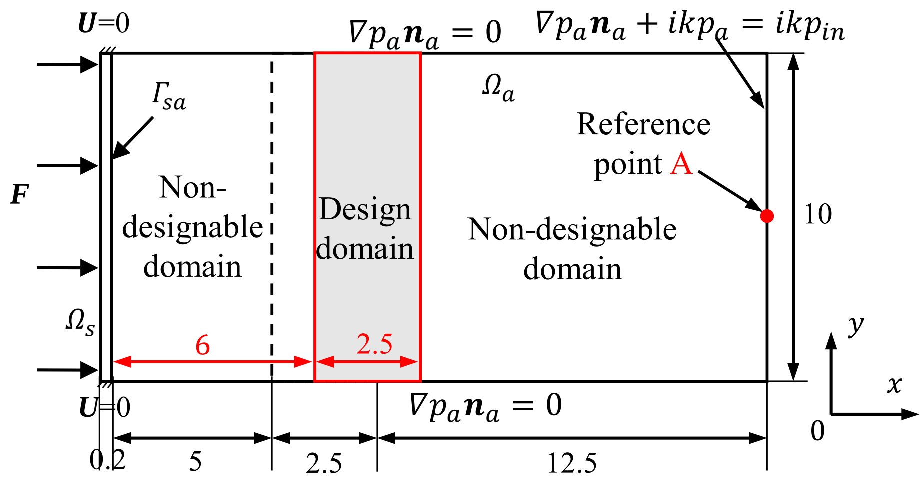

Figure 8: The adjusted 2D acoustic structure.

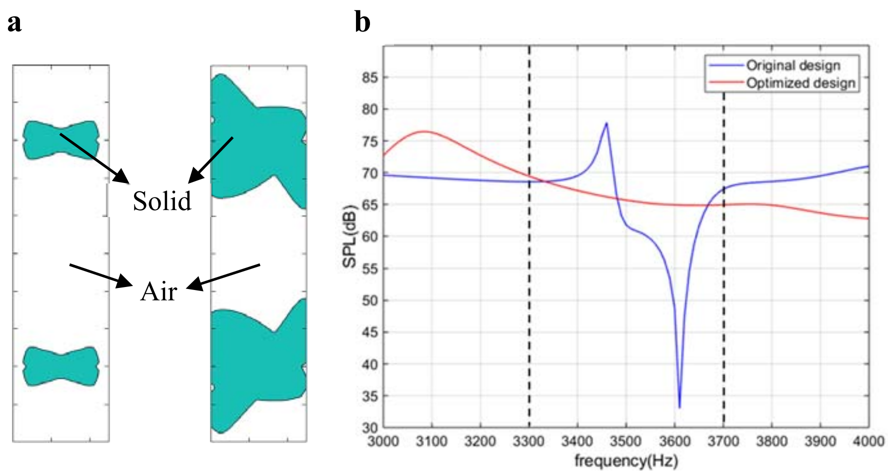

Figure 9: (a) The initial distribution of the components and the optimized structure; (b) SPL curves of the original structure and the optimized structure ([3000Hz, 4000Hz])

4 Conclusions and Contributions

In this paper, a new agent model based on deep learning and deep transfer learning is proposed to quickly and accurately predict the acoustic pressure frequency response of acoustic structures in different environments, solving the multi-frequency calculation difficulty and the time cost problem caused by the calculation of homogeneous and heterogeneous structures in the sound quality optimization problem. In the sound quality optimization, the high-precision DNN replaces the finite element model and significantly improves the computational efficiency in the sound pressure frequency response calculation and optimization iterations. Under the deep transfer learning framework, the DNN can be quickly applied to the corresponding homogeneous heterogeneous structures by transfer learning from small sample data. In the face of structural designs with large variations, the DNN can still have high prediction accuracy after multiple stepwise migration learning. The numerical examples given verify that the DNN based on deep transfer learning works well in different acoustic optimization tasks, which provides a strong technical guarantee for the design and optimization of acoustic devices. The fast and accurate prediction performance of the proposed method can provide a sufficient number of validation solutions in a short period of time for tasks that would otherwise require significant time costs, which is very promising for applications in engineering production.

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