Accelerated topological design of metaporous materials of broadband sound absorption performance by generative adversarial networks

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**Highlights**
- GANs newly used for topological design of metaporous materials for sound absorption.
- Huge acceleration (~0.04s/design) for design process enabling instantaneous designing.
- Successful designs of broadband sound absorption checked by simulation and experiment.
- Creative configurations and rich local features generated in GANs-designed patterns.
- AI-guided designing/optimizing as new possibility for AI-materials interdiscipline.

**Abstract**
The topological design and optimization of metaporous materials is one of the key challenges in the field of sound absorption. Limited by the expensive computational cost, it is particularly disadvantaged when instantaneous multiple designs are required. In recent years, an increasing number of research fields are harnessing machine learning approaches thanks to their experience-free manner and outstanding efficiency. Generative Adversarial Networks (GANs), as a type of machine learning algorithms, enjoy the special benefit of powerful generative capability, making them brilliantly suitable for designing purposes. Additionally, it can fully explore the data distribution space with enormous computational power and create brand new designs. In this work, GANs are newly employed for the topological design of metaporous materials for sound absorption. Trained with numerically prepared data, they successfully propose designs with high-standard broadband absorption performance, verified by simulation and experiment. The designing process is dramatically accelerated by hundreds of times using GANs (100 designs in 4.372 s). This allows GANs to easily provide more structures and configurations and achieve instantaneous multiple solutions, giving designers more choices to satisfy various constraints such as mass or porosity. In addition, GANs are demonstrated remarkably capable of generating creative configurations and rich local features. This work proposes a new designing principle, illustrates the value of machine learning in guiding the designing and optimizing process in the mechanical world, and opens new possibilities for the future of AI-materials interdisciplinary research.

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1. Introduction

Materials for high-efficient airborne-sound absorption have been extensively pursued for decades. Classical porous materials, e.g., foam, glass fiber and mineral wool, are unsuitable for low frequency sound absorption as bulky and heavy materials are required in this case [1]. To overcome the shortcoming of the classic porous materials, using metaporous materials, i.e., a porous matrix embedded with inner scatterers, provides a promising alternative. The last twenty years has seen a growing number of works devoted to the designing of metaporous materials [2–10].

However, limited by intuition, the reported designs feature mostly regular shapes, leaving the potential of the metaporous materials largely unexploited. As an inverse design strategy, topology optimization was capable of producing more complex designs that achieve far more enhanced absorption at multiple target frequencies owing to the possession of different resonance mechanisms in the same design [11]. Nevertheless, the existing topology optimization methods suffer inherent drawbacks in terms of computational time and cost due to extensive variables and numerous iterations needed. Particularly, it becomes even more expensive if a number of designs are required. Moreover, instantaneous designing is hardly possible. To this end, the emerging machine learning algorithms are considered to possess great potential to substantially boost the efficiency of designing and exploring new topologies.

The last decade has witnessed the booming of machine learning technology. It has become not only popular in computer science related subjects but also other fields such as mechanics, biology and material science [12–22]. It enjoys the advantage of being an experience-free approach as well as allowing instantaneous multiple designs simultaneously with extremely high efficiency [23]. In addition, it has been favorable for its capability of discovering complex intrinsic pattern of large datasets with the prevailing big data era [13]. To the best of our knowledge, machine learning methods have so far not been employed for the design of sound absorption materials. However, we are seeing a rising trend of machine-learning-based designing of two-dimension (2D) architectures [24]. He et al. achieved inverse design of topological metaplates for flexural waves through finding the non-linear mapping between the key parameters and the topology via neural networks [23]. A framework integrating topology optimization and generative models was proposed and validated on the case of 2D wheel design using Boundary Equilibrium Generative Adversarial Networks (GANs) [25]. A convolutional neural network (CNN)-based encoder and decoder network together with conditional GANs was employed as a two-stage refinement to realize near-optimal topological design [26].

Most of the existing works on topological design or optimization adopt basic convolutional neural networks. Those algorithms are usually effective at indirectly designing the structure by deciding its individual parameters (such as the length of an edge or the radius of a circle), but can hardly make a sophisticated design based on complete patterns. As a contrast, our work can directly generate topological patterns using a generative network - GANs. GANs feature a generator and a discriminator that learn simultaneously in competition with each other [27,28]. The generator can generate brand new data (e.g. the topological structure of metaporous materials in this paper) based on the captured potential distribution of the training data. Since the generator is extraordinarily powerful computationally, it can thoroughly explore the data space and produce creative designs that potentially exceed the limitation of the existing ones. Previous works have successfully employed GANs to obtain over 400 complex two-dimensional architectures that approach the Hashin-Shtrikman upper bounds [29]. Conditional GANs were used to design nanophotonic antennae with desired optical properties [30].

In this paper, GANs are employed to carry out topological design of metaporous materials for sound absorption in a significantly accelerated and efficient manner. Trained with numerically prepared data, GANs are demonstrated capable of generating designs with high-standard broadband absorption performance, verified by Finite Element Modeling (FEM) simulation and experiment. Meantime, brand new configurations and local features are seen in the designs by GANs, illustrating its ability of 'creativity' and potential to further improve the existing materials for enhanced performance.

2. Dataset

The training set prepared with FEM simulation consists of 1832 images of \(a \times a = 64 \times 64\) pixels. Each image represents a pattern for metaporous material. Typical patterns are shown in Fig. 1 where the solid black domain denotes the scatterer and the white area is filled with porous media. The patterns are stored as binary images composed of 0 and 1, corresponding to porous media and scatterer, respectively. The shapes of the scatterer in the training set are composed of three types of basic primitives, i.e., slotted cube, slotted elliptic cylinder and thin partitions. For the slotted cube, the lower (upper) bounds of the outer side lengths and slot width are 0.4a (0.8a) and 0.08a (0.48a), respectively. The minimum (maximum) lengths of outer semi-axis and slot are 0.2a (0.48a) and 0.08a (0.48a) for the slotted elliptic cylinder. As for the thin partition, the lower and the upper bounds of the length are respectively 0.2a and 0.8a. The thickness for all three primitives is no larger than 0.0625a. The generation procedure for all the patterns starts from a porous media (64 × 64 null matrix). The scatterer is subsequently ‘embedded’ into the porous media at a random location, imitating the mutation process in the genetic algorithm [31], i.e., some pixels of porous media (0) are changed to that of scatterer (1). To increase the diversity of the patterns, a perturbation operator is applied to the pattern where the pixels inside the scatterer are reversed with 20% probability. Finally, in order to improve the geometric topology and eliminate checkerboard pattern, the abtual filter is employed [32], i.e., some isolated porous elements are changed to scatterer elements and vice versa.

![Fig. 1. Typical patterns in the training set.](image-url)
The patterns in the training data contain up to three primitives. Fig. 1(a)-(d) plots those with only one primitive. The employment of perturbation operator during the generation process leads to the non-smooth peripheries of the slotted scatterer as well as the discrete dotted black pixels inside. It is also the reason for the existence of the closed cylinder shown in Fig. 1(c). The patterns consisting two or three primitives are shown in Fig. 1(e)-(l). For instance, Fig. 1(e) and Fig. 1(g) show the patterns with two primitives of the same type. The examples for multiple primitives with different types are given in Fig. 1(k) and (l). Particularly, we shall pay attention to the correlation between primitives in the same pattern. They can be simply apart as in Fig. 1(g), half intersected in Fig. 1(f) or internally tangent in Fig. 1(h).

To obtain the absorption coefficients of each pattern, full-wave simulation is performed via Pressure Acoustic and Frequency domain module with the commercial finite element software COMSOL®. As shown in Fig. 2, a plane wave is incident to the pattern with the amplitude of 1 Pa from the background pressure field. Perfectly matched layer (PML) is applied at the left boundary of the background pressure field to simulate anechoic termination for outgoing wave (i.e., reflective wave). The horizontal black dashed lines denote the periodic boundary while the green black solid line at the right end is the hard acoustic boundary. The porous media in the metaporous material is melamine foam as in our previous work [9]. The acoustic parameters of the melamine foam are described using Johnson-Champoux-Allard (JCA) model [33] in Poroacoustics Domain, as listed in Table 1, where \( \Phi \) is the porosity, \( \sigma \) the flow resistivity, \( \alpha \), the tortuosity, \( \lambda \) the viscous length and \( \lambda' \) the thermal characteristic length. The sample frequencies in the simulation are from 300 Hz to 3000 Hz at the interval of 50 Hz. Since GANs generate new patterns based on what they are feed with, we prepared 1832 patterns whose average absorption coefficients are larger than 0.9 to form the training set, aiming to obtain patterns with at least equally high absorption performance.

3. Methods

3.1. Generative adversarial networks

GANs feature a pair of networks, a generator G and a discriminator D, competing with each other. As a two-player zero-sum game, G aims to generator ‘fake’ data that are as ‘real’ as possible to ‘fool’ G, while G learns to discriminate fake data generated by G from real ones as accurately as possible. This is essentially a min-max process where G and D can both respectively sharpen their generative and discriminative skills [34]. Importantly, G does not directly access real images and it learns only through interacting with D [28]. Consequently, G learns to generate usable data (patterns in our case) for the purpose of the specific model setup. Eventually, a Nash equilibrium is reached, meaning each player cannot obtain a better result without changing the other players’ strategy, and two players stay equally good [35].
3.2. Design procedures

Fig. 3 demonstrates the procedure to design and verify the metaporous materials. Three main steps are necessary for a complete and reliable design: 1) training data preparation; 2) generating designs using trained GANs; 3) verify those designs with FEM simulation and experiments.

The left part of Fig. 3 shows the design procedures of metaporous materials with GANs in this work. The model is built with Pytorch. Pytorch is a commonly used open-source deep learning framework, basically a library that provides building blocks for designing, training and validating deep neural networks via a high-level programming interface [36,37]. Being a python library, Pytorch enjoys the advantages of possessing both GPU-accelerated tensor computation and performance at the same time. With packages from Pytorch, procedures in deep learning such as network building and gradient descent can be programmed with a couple of code lines, making it far more efficient.

In general, the architectures of G and D are described as follows. The input of G is a greyscale image with 64 x 64 size. G contains ten convolutional layers. Each convolutional layer is followed by a batch normalization layer and a ReLU layer. The output of G is still a grey image with the same size as the input one. D takes the grey image generated by G as the input. D consists of five convolutional layers and a softmax layer. Each convolutional layer is also followed by a ReLU layer. The output of D is a binary classification label which indicates if the generated image is legitimate or not.

Fig. 4. Designs proposed by GANs and their absorption performance simulated by FEM: (a) I: designs 1–4; (b) II: designs 5–8; (c) Absorption coefficients of Design 1–4; (d) Absorption coefficients of Design 5–8.
Specifically, with a random noise (64 × 64 size) as input, G outputs a ‘fake’ pattern (64 × 64 size) which is subsequently input into D together with the ‘real’ patterns – the training data. D judges whether the generated pattern is legitimate by comparing it with training data. With the advancement of the minmax process, G finally learns to generate designs that are comparable with the training data. Delightfully, patterns generated this way possess new features since G is computationally extremely powerful to explore the full distribution of the data space (i.e., full possibilities).

Note that the criterion of D’s judgement on whether a pattern is legitimate or not is actually learned via training, instead of adopting a handcrafted criterion. The criterion is essentially represented by the weights in the convolutional kernels that are constantly applied to the input images to extract features at each convolutional layer in the neural networks. Starting with a random D with a cross-entropy loss that calculates the difference between the output pattern of the G with the input pattern, D’s aim is to maximize the loss while G’s aim is to minimize it, which forms a minmax ‘competition’. D’s capability of judging whether the generated pattern is legitimate is basically equal to its capability to maximize the loss, which relies on the choice of weights. The same logic goes to G’s capability of generating legitimate patterns. During training, the ‘competition’ advances, where D and G continuously adjusts their own weights based on the loss until a balance is reached (i.e. the Nash equilibrium). Eventually, a capable D is obtained with a set of learned weights to represent the criterion that is good at ‘judging’.

4. Results

4.1. GANs-designed patterns and numerical verification

GANs bring extreme acceleration of the designing process, enhancing the efficiency by hundreds of times compared with

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![Fig. 5. Pressure distribution inside Design 3 at the characteristic frequencies of: (a) $f_1 = 950$ Hz; (b) $f_2 = 1300$ Hz; (c) $f_3 = 1960$ Hz; (d) $f_4 = 2600$ Hz.](image)
the existing approaches such as density-based approach and genetic algorithm [38]. The generation of 100 patterns takes approximately only 4.372 s (with commonly used Nvidia RTX3090) once the model is well trained. More details regarding the time needed for data preparation and model training are described in Appendix A.

More than a hundred designs of metaporous materials are proposed by GANs out of which eight typical ones are presented in Fig. 4. The height and the width of a pattern are both 64 mm (and 64 pixels). So, one pixel inside the pattern has the size of 1 mm × 1 mm. Overall, all the designs can be classified into two categories: I - multiple slotted cavities with different orientations and creative variation on the periphery (Design 1–4 in Fig. 4(a)); II - a single slotted cavity with large opening and rich local features inside (Design 5–8 in Fig. 4(b)). Note that ‘annulus’ here is a general term describing the circle-like or rectangle-like outlines in the pattern. Additionally, to differentiate GAN-generated patterns from the training data, patterns below are highlighted in blue (scatterer) and pink (foam).

The FEM-calculated absorption coefficient curves of the eight designs are illustrated in Fig. 4(c) and (d). Overall, all the eight designs show broadband absorption capability. The average absorption coefficients (between 300 Hz and 3000 Hz with the interval of 50 Hz) are listed in Table 2. It is shown that the average absorption coefficients of all designs are larger than 0.925, which is a rather high standard.

![Image](image_url)

It is illustrated that GANs are skilled at generating and alternating local features. Being greatly capable at manipulating input information, it can comprehensively assemble different shapes/primitives in creative configurations. For instance, the model has learned from Fig. 1(h) that one primitive can be inside another one. Meanwhile, it has captured several different primitives out of the training data including slotted cylinders and thin rigid partitions. Design 5 in Fig. 4(b) is a result of putting thin partitions inside a slotted cylinder as well as making some modification and variation on the cylinder’s periphery. Hence, we reckon that GANs are capable of capturing different shapes in the training data, treating them as separate features and generating brand new combinations and create rich variation on the features themselves.

Particularly noteworthy is the position of the opening on the cavity. The training data only contain patterns with opening positioned towards the incident end of the sound wave, i.e., the top of the pattern. However, GANs have created new opening positions towards the backing (the bottom of the pattern) as shown in Design 3 and 4 in Fig. 4(a). This operation is of great importance for sound absorption and is often highlighted in the existing non-machine-learning-based designing methods [39].

4.2. Broadband absorption mechanism

To explore the mechanism behind the broadband absorption performance, we choose Design 3 and Design 8 as representatives.
of the two categories of designs for deeper examination. Fig. 5(a)-
Fig. 6(d) plot the pressure distribution of Design 3 at four character-
istic frequencies. It is noted that the two slotted cylinders are sole 'active' at the frequencies of \( f_1 \) and \( f_3 \), i.e., maximum pressure is located at the two slotted cylinders and resonance state exists near the two frequencies. At the frequency of \( f_2 \), the pressure is trapped between the two slotted cylinders and the backing, while both two slotted cylinders are simultaneously 'active'. However, Design 3 shows a different coupled mode at the frequency of \( f_4 \). Notable acoustic scattering is observed between the two slotted cylinders near the incident end and partial acoustic energy also enters the left slotted cylinder. It could be concluded that the collaboration of resonance, acoustic trapping and scattering effect contributes to the overall broadband absorption of Design 3.

Fig. 6(a)-(d) further illustrates the pressure distributions of Design 8 at four representative frequencies. At low frequency \( f_1 \),
the main acoustic energy enters the full big cavity while partially trapped between the cavity and the backing. At frequencies \( f_2 \) and \( f_3 \), it is interesting to note that two different local resonance modes are triggered by the thin partitions inside the cavity. The two local resonance modes together with the scattering outside the cavity also contribute to the sound absorption of Design 8 at frequency \( f_3 \). Different from Design 3, Design 8 possesses more complex local modes inside the cavity; thanks to the rich local features of thin partition generated by GANs.

4.3. Experimental verification

Fig. 7 illustrates the process of sample preparation. Overall, the metaporous material is composed of three components, i.e., a cover layer, an inner scatterer and melamine foam. The inner scatterer and the cover layer are 3D printed with polylactic acid (PLA) with the parameters of density \( \rho = 1250 \text{ kg/m}^3 \), Young’s modulus \( E = 1.2 \text{ GPa} \) and Poisson’s ratio \( \nu = 0.35 \). The thickness of the cover layer is 1 mm. Compared with the size of the cubic sample 60 mm, the influence of the cover layer is neglectable. To facilitate the embedding of the scatterer, a pattern with the shape of the scatterer is etched into the melamine foam. The metaporous material is an assembly of all the components. Note that the sound wave is incident into the top face along the -y direction shown in Fig. 7.

The experiment is carried out in a home-made impedance tube using the two-microphone method [40]. As shown in Fig. 8(a), the impedance tube features a square cross-section with the side length of \( d = 60 \text{ mm} \). The sample is attached to a rigid backing. The distances between the sample and the two microphones are \( L_1 = 200 \text{ mm} \) and \( L_2 = 150 \text{ mm} \), respectively.

Design 3 and Design 8 are chosen for experimental verification. Fig. 9(a) and (b) compare results obtained by the experiment and FEM simulation. Overall, a good agreement is reached. However, some discrepancies still exist, especially for Design 8. We consider that the mismatch is a result of two reasons: (1) the uncertainty of fabrication for both 3D-printed frame and the etched melamine foam; (2) the inaccuracies occurred during the assembling process.

5. Conclusions

In this work, GANs are used to design metaporous materials for sound absorption. The training set is prepared with FEM simulation, containing 1832 binary images of \( 64 \times 64 \text{ pixels} \). With Pytorch framework, trained GANs can generate 100 patterns in roughly 4.372 s, bringing tremendous acceleration of the designing process, boosting the efficiency by hundreds of times compared with the existing approaches. Eight typical designs proposed by GANs are chosen to be verified by FEM simulation, out of which two are printed out with a 3D printer for experimental evaluation. The advantage in the computation time enables this approach to provide more structures and configurations, and achieve instantaneous multiple solutions with high absorption performance, compared to a unique solution as the case with the existing methods.

The results illustrate that GANs are capable of generating metaporous material designs with satisfying broadband absorption performance. The FEM simulation of the eight designs demonstrated that their average absorption coefficients are all larger than 0.925. The experiments again confirm the quality of the two 3D printed designs. Additionally, the numerical and experimental results show satisfying agreement.

As to the generative capability, GANs are demonstrated skilled at capturing input information and generating brand new configurations and rich local features comprehensively. Two typical creations of GANs’ are observed. One is to learn a new assembling approach and alternating primitives (as well as adding local features) for the assembly to form a new design. The other is that GANs have created new opening positions for the design, which is of crucial significance in practice.

Overall, this work has for the first time utilized GANs to design metaporous materials for sound absorption. The accelerated designing process and the satisfying results demonstrate that AI-materials interdisciplinary approach is of excellent potential and importance in guiding the designing and optimizing process in the mechanical world.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Computation time

The 1832 patterns with \( >0.9 \) average absorption coefficients are selected from a larger database with 7636 patterns in total via examining all their average absorption coefficients. That means we use COMSOL (full-wave simulation) to calculate the average absorption coefficient of all the 7636 patterns. Each calculation takes about 3 s, making it 22,908 s (that’s roughly 382 min or 6.36 h) in total. Note that the 7636 patterns are generated following the generation procedure described in ‘section 2 Dataset’, which is rather fast. The generation of 7636 patterns takes around 234.7 s (roughly 3.9 min) in total. So, the preparation of the training dataset of 1832 patterns takes approximately 386 min (~6.43 h), including 2 parts: the generation of 7636 patterns (3.9 min) and the COMSOL FEM calculation of 7636 patterns (382 min).

Model training time is related to the GPU computation power. With NVIDIA RTX3090, the whole training takes about 8 h. The training process can easily speed up via training in parallel on multiple GPUs.

In total, the pre-designing stage (including training set preparation and model training) need <15 h.

On the other hand, based on our experience of the existing topology optimization methods, one generation averagely takes about 3 s and it needs around 200 generations for the algorithm to converge to give out a design, i.e. 600 s for one pattern. Therefore, to design 100 well-performed patterns with genetic algorithms takes about 1000 min (~16.7 h), which is already longer than the GANs-based approach. The above comparison is only for designing 100 patterns. When more patterns are needed, the advantage of GANs-based approach becomes a lot more obvious as it only needs multiple seconds (for generation) while the existing methods need hours.

Therefore, the GANs-based approach has dramatically accelerated the designing procedure especially when instantaneous multiple solutions are needed.

Data availability

The raw/processed data required to reproduce these findings cannot be shared at this time as the data also forms part of an ongoing study.