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Deep learning enables accurate sound redistribution via nonlocal metasurfaces

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Abstract

Conventional acoustic metasurfaces are constructed with gradiently “local” phase shift profiles provided by subunits. The local strategy implies the ignorance of the mutual coupling between subunits, which limits the efficiency of targeted sound manipulation, especially in complex environments. By taking into account the “nonlocal” interaction among subunits, nonlocal metasurface offers an opportunity for accurate control of sound propagation, but the requirement of the consideration of gathering coupling among all subunits, not just the nearest-neighbor coupling, greatly increases the complexity of the system and therefore hinders the explorations of functionalities of nonlocal metasurfaces. In this work, empowered by deep learning algorithms, the complex gathering coupling can be learned efficiently from the preset dataset so that the functionalities of nonlocal metasurfaces can be significantly uncovered. As an example, we demonstrate that nonlocal metasurfaces, which can redirect an incident wave into multi-channel reflections with arbitrary energy ratios, can be accurately predicted by deep learning algorithms. Compared to the theory, the relative error of the energy ratios is less than 1%. Furthermore, experiments witness three-channel reflection with three types of energy ratios of $(1, 0, 0)$, $(1/2, 0, 1/2)$, and $(1/3, 1/3, 1/3)$, proving the validity of the deep learning enabled nonlocal metasurfaces. Our work might blaze a new trail in the design of acoustic functional devices, especially for the cases containing complex wave-matter interactions.

7 The emergence of acoustic metamaterials, which are artificial materials with targeted function-
 8 alities, have significantly broaden the fields of physical and material science^{1–6}. Novel acoustic
 9 manipulations based on metamaterials have been realized, such as acoustic focusing^{7–9}, acous-
 10 tic cloaking^{10–12}, acoustic holography^{13–15}, and asymmetric acoustic transmission^{16–19}. In the
 11 last decade, acoustic metasurfaces, as 2D acoustic metamaterials, stand out as distinct choices
 12 to manipulate sound for their vanishing thickness^{20–32}. By employing “locally” designed phase
 13 shift provided by subunits of metasurfaces, fascinating acoustic manipulations are extensively
 14 explored recently, including acoustic cloaking³³, acoustic holography¹⁵, and compact sound
 15 absorbers^{26,34–36}. However, in the most of previous designs, the subunits are designed indi-
 16 vidually according to the discretized phase shift profile. In this way, the mutual coupling among
 17 the subunits which also contributes the wave-field forming is neglected. It therefore turns out
 18 that the designed metasurfaces suffer from the lower efficiency, especially in the cases where
 19 incident/reflected/transmitted angles are relatively large. Furthermore, to reshape wave field with
 20 fine resolution, a large number of subunits are necessary which inevitably introduce undesired
 21 loss due to the viscous-thermal effect induced by small apertures in small subunits. Recently,
 22 the concept of “nonlocal” metasurface is introduced to overcome these limitations^{37–40}. In these
 23 works, the nonlocal coupling effects among all subunits are taken into account to collect the
 24 contribution of nonlocality to the wave-field forming and therefore give rise to more accurate
 25 wave field manipulations. However, it also makes the nonlocal system quite complex and the
 26 relationship between desired wave field and the geometrical parameters unclear. In this situation,
 27 optimization methods are generally employed to inversely design the functionality of nonlocal
 28 metasurface. However, for different wave manipulation aims, the objective function needs to be
 29 revised correspondingly to search for the best value in the entire parameter space, resulting in the
 30 drawbacks of time-wasting and computational resource-consuming.

31 The development of artificial intelligence algorithms provides new insights into the inverse de-
 32 sign of nonlocal metasurfaces. In view of its extreme success in domains correlated to the detection
 33 of diseases^{41,42}, speech recognition⁴³, computer vision⁴⁴, and natural language processing^{45,46},
 34 deep learning has aroused wide attention. The excellent learning and inference capabilities of
 35 deep learning enable it to achieve the similar effect of logical calculations with physical formulas.
 36 Many works about combining deep learning with physics have been attempted, including opti-
 37 mization of photonic structures^{47–53}, high-resolution imaging^{54,55}, and acoustic source imaging⁵⁶.

38 In this work, by harnessing the power of deep learning, we explore the capabilities of reshap-

FIG. 1. The schematic diagram of nonlocal acoustic metasurface. The metasurface is composed of repeated supercell along x direction with a period of a . Three grooves are etched in each supercell. t_l and h_l represent the width and the depth of the l th groove, and dx_l refers to the distance between adjacent grooves ($l = 1, 2, 3$). The incident wave along the $-y$ direction could be reflected to three allowed diffracted beams.

ing acoustic fields accurately by nonlocal metasurfaces. The complex nonlocal coupling can be learned by deep learning efficiently from the preset datasets. Then for a target wave field, deep learning can predict the structural parameters of a nonlocal metasurface in a few seconds. In the following, we will demonstrate that nonlocal metasurfaces predicted by deep learning can redirect an incident wave into multi-channel reflections with arbitrary energy ratios. Compared to the direct calculations, the relative error of the energy ratios is less than 1%. In addition, we also perform experiments to witness the ability of the deep learning enabled nonlocal metasurfaces.

Results

Theory of nonlocal metasurface. Our proposed nonlocal metasurface is schematically shown in Fig. 1, which consists of a suitable engineered arrangement of grooves. In this work, we set 3 rectangular-shaped grooves in each period to demonstrate the ability of energy redistribution among three allowed diffraction beams. We will show that empowered by machine learning algorithms, the energy proportion of the three diffracted beams can be redistributed arbitrarily by tuning the depth (h_l) and the width (t_l) of each groove and the distance between two adjacent grooves (dx_l).

When an incident acoustic plane wave along with $-y$ direction impinges on the metasurface (i.e., incident angle $\theta_i = 0^\circ$), the periodicity of the metasurface will give rise to a set of different diffraction modes. According to the coupled mode theory, the pressure field $p(x, y)$ and normal

58 velocity field $v(x, y)$ in the region above the structure (Region I) can be expressed by⁴⁰

$$p_I(x, y) = A_0^+ e^{jk_0 y} + \sum_n A_n^- e^{-jk_{x,n} x} e^{-jk_{y,n} y}, \quad (1)$$

59

$$v_I(x, y) = -\frac{A_0^+}{\rho \omega} k_0 \cdot e^{-jk_0 y} + \sum_n \frac{A_n^-}{\rho \omega} k_{y,n} \cdot e^{-jk_{x,n} x} e^{-jk_{y,n} y}, \quad (2)$$

60 where A_0^+ , A_n^- are the amplitude of the incident wave and the n th-order of the reflected diffraction
 61 beams. $k_{x,n} = k_0 \sin \theta_i + G_n$, and $k_{y,n} = \sqrt{k_0^2 - k_{x,n}^2}$, are the x and y component of the n th-order
 62 diffraction wave vector with k_0 being the wave number of incident waves and $G_n = n2\pi/a$ rep-
 63 resenting the reciprocal lattice vector. ρ and ω refer to the mass density of the medium and the
 64 angular frequency. From the above formulas, the period a of the metasurface related to $k_{x,n}$ decides
 65 the propagation characteristics of different diffraction modes. It means that by selecting a suitable
 66 a , the numbers of the allowed propagating diffraction orders can be tuned.

67 To illustrate the nonlocal coupling effect among etched grooves, we need first get the pressure
 68 and velocity field inside each grooves. Considering the fact that the bottom of the grooves are
 69 acoustically hard where the normal velocity should be zero, the $p(x, y)$ and $v(x, y)$ in grooves
 70 (Region II) could be represented as

$$p_{II}^l(x, y) = \sum_k a_{kl} \cos[\alpha_{kl}(x - x_l)](e^{j\beta_{kl} y} + e^{-j\beta_{kl}(y+2h_l)}), \quad (3)$$

71

$$v_{II}^l(x, y) = \sum_k -\frac{a_{kl}}{\rho \omega} \beta_{kl} \cos[\alpha_{kl}(x - x_l)](e^{j\beta_{kl} y} - e^{-j\beta_{kl}(y+2h_l)}) \quad (4)$$

72 where a_{kl} represents the amplitude of the k th-order of the waveguide mode, x_l is the beginning x
 73 coordination of the l th groove, $\alpha_{kl} = k\pi/t_l$ and $\beta_{kl} = \sqrt{k_0^2 - \alpha_{kl}^2}$ are the x and y components of
 74 the wave vector for the k th-order mode in the groove, respectively. Conforming to the conditions
 75 at the air-metasurface interface, sound pressure and volume velocity should be continuous at $y = 0$.
 76 By plugging Eqs. (1)-(4) into continuum conditions and integrating the equations with orthogonal
 77 relationship, we can get the following equations:

$$\begin{pmatrix} P_1^1 \\ P_1^2 \\ P_1^3 \end{pmatrix} A_0^+ + \begin{pmatrix} P_2^1 \\ P_2^2 \\ P_2^3 \end{pmatrix} A_n^- = \begin{pmatrix} P_3^1 & 0 & 0 \\ 0 & P_3^2 & 0 \\ 0 & 0 & P_3^3 \end{pmatrix} \begin{pmatrix} a_{kl}^1 \\ a_{kl}^2 \\ a_{kl}^3 \end{pmatrix}, \quad (5)$$

78 and

$$V_1 A_0^+ + V_2 A_n^- = \begin{pmatrix} V_3^1 & V_3^2 & V_3^3 \end{pmatrix} \begin{pmatrix} a_{kl}^1 \\ a_{kl}^2 \\ a_{kl}^3 \end{pmatrix}, \quad (6)$$

79 where

$$P_1^l(k) = \frac{1}{t_l} \int_{x_l}^{x_l+t_l} \cos \alpha_{kl}(x-x_l) dx, \quad (7)$$

$$P_2^l(k, n) = \frac{1}{t_l} \int_{x_l}^{x_l+t_l} e^{-jk_{x,n}x} \cos \alpha_{kl}(x-x_l) dx, \quad (8)$$

$$P_3^l(k_1, k_2) = (1 + e^{-j2\beta_{k_1}h_l}) \frac{1}{t_l} \int_{x_l}^{x_l+t_l} \cos \alpha_{k_1l}(x-x_l) \cos \alpha_{k_2l}(x-x_l) dx, \quad (9)$$

$$V_1(m) = -\frac{1}{a} \int_0^a k_{y,0} e^{jk_{x,m}x} dx, \quad (10)$$

$$V_2(m, n) = \frac{1}{a} \int_0^a k_{y,n} e^{-j(k_{x,n}-k_{x,m})x} dx, \quad (11)$$

84 and

$$V_3^l(m, k) = -(1 + e^{-j2\beta_{kl}h_l}) \frac{\beta_{kl}}{a} \int_{x_l}^{x_l+t_l} \cos \alpha_{kl}(x-x_l) e^{jk_{x,m}x} dx, \quad (12)$$

85 with $m, n = 0, \pm 1, \dots, \pm(N-1)/2$ and $k, k_1, k_2 = 1, \dots, K$. P_1^l, P_2^l, P_3^l are respectively related to
 86 the the sound pressure of incident wave, reflected wave in Region I and the sound wave in Region
 87 II. And their dimensions are known as $LK \times 1, LK \times N$ and $LK \times LK$. L is the total number of grooves
 88 in a period, K is the total number of modes inside the metasurface, and N is the total number of
 89 diffraction modes. In fact, the superscript and subscript of V have the similar meaning as those of
 90 P , but V is related to the volume velocity of sound waves. The dimensions of V_1, V_2, V_3^l are $N \times 1,$
 91 $N \times N, N \times LK$ respectively. We simplify the above equations with matrixes and rewrite them as:

$$\begin{pmatrix} P_1 \\ V_1 \end{pmatrix} A_0^+ = \begin{pmatrix} -P_2 & P_3 \\ -V_2 & V_3 \end{pmatrix} \begin{pmatrix} A_n^- \\ a_{kl} \end{pmatrix}, \quad (13)$$

92 From Eq. (13), the reflected energy of each diffraction order could be calculated. In order to show
 93 energy distribution intuitively, we utilize $I = \left| \frac{A_n^-}{A_0^+} \right|^2 \cos \theta_r$ to denote the power flow ratio of each
 94 mode. Here, we choose -1st, 0th and +1st order diffractive components as reflected channels, and
 95 the corresponding diffraction angles for them are $\theta_r = -60^\circ, 0^\circ, 60^\circ$. The working frequency is set
 96 to $f_0 = 8000\text{Hz}$. In real situations, the harmonic modes of the metasurface and its internal modes
 97 are very complicated, so we choose $K=20, N=51, L=3$ to be as close to the actual situations as
 98 possible. Obviously, the consideration of non-locality makes the dimension of the matrixes large
 99 which means that the computational complexity is higher. This brings more troubles to inverse
 100 design.

101 **Deep learning model.** The special operating mechanism of deep learning will help to explore
 102 the relationship between metasurface and its response to acoustic waves. Here, we establish a

FIG. 2. Schematic representation of data acquisition and the tandem network. This network is composed of pre-trained forward network A_{net} (in the red dotted box) and inverse network B_{net} (in the blue dotted box). The intermediate layer where the blue nodes are located is the output layer of the inverse design.

103 tool that can achieve rapid forward and inverse design with the support of deep learning. This
 104 part of content mainly explains the process of building the transient reactor through deep learning
 106 algorithms (the specific training mechanism can be found in the Method).

107 To realize the intelligent design of metasurfaces, we firstly should establish a data set. We
 108 introduce a vector $\mathbf{S} = (h_1, h_2, h_3, t_1, t_2, t_3, dx_1, dx_2)^T$ which is composed of the structure parameters
 109 of metasurfaces. Meanwhile, reflected power flow ratio in three channels is expressed as a state
 110 vector $\mathbf{I} = (I_1, I_2, I_3)^T$, where I_1, I_2, I_3 respectively correspond to power flow of -1 st, 0 th and $+1$ st
 111 order diffractive components. The dataset based on diffraction theory for metasurfaces contains
 112 many arrays $\{\mathbf{S}, \mathbf{I}\}$, including 270,000 training samples and 30000 test samples. Specifically, as
 113 shown in Fig. 2, we randomly generate many different sets of $\mathbf{S}$ and calculate their corresponding
 114 $\mathbf{I}$ by MATLAB. Here, we construct two network models (A_{net} and B_{net}), one of which takes $\mathbf{S}$ as
 115 input data and $\mathbf{I}$ as label data while the other is the opposite. Obviously, there is a correspondence
 116 between these two vectors, $\mathbf{I} = A_{net}(\mathbf{S})$, $\mathbf{S} = B_{net}(\mathbf{I})$, where A_{net} is the forward deep learning network
 117 and B_{net} is the inverse neural network. It should be noted that B_{net} can hardly converge when it
 118 is trained in a similar way as A_{net} since the same power-flow distribution could be accounted for

different arrangement of meta-units.

To tackle this multi-value problem, we exploit tandem neural network introduced in Ref.⁴⁷. As Fig. 2 shows, the tandem network model is composed of A_{net} and B_{net} , which connects the trained A_{net} served as a backend behind the B_{net} . This connected network is similar to an autoencoder network (consists of two networks: encoder and decoder) in terms of structures, in which the input data in the first layer has the same physical meaning as the data in the final layer and structural parameters exist as the encoded feature data in the intermediate layer. The entire network trained successfully is actually a transient reactor. In the construction of it, the forward network with dataset $\{\mathbf{S}, \mathbf{I}\}$ is supposed to be trained as the pre-trained network firstly. Then, when training the connected model, $\mathbf{I}$ is both the input data and the target value that needs to be compared with the output data. Different from the general autoencoder training mechanism which is often used for unsupervised learning, we have a prepared dataset including label data, so we can train the “decoder” (A_{net}) first. Training part of the network in advance transforms the surjective relation between $\mathbf{S}$ and $\mathbf{I}$ into bijective relation, and in this way, the root cause of the failure to converge inverse network is resolved.

For all training processes, Adaptive Moment Estimation (Adam) optimizer⁵⁷ is chosen as the global optimizer. Forward training is done by minimizing the cost function, $C_1 = \frac{1}{N} \sum |\mathbf{I}_{true} - \mathbf{I}_{pred}|$, in which N is the batch size of training dataset, $\mathbf{I}_{pred}$ is the possible power flow ratio predicted by A_{net} and $\mathbf{I}_{true}$ is the target value in dataset. The value of cost function is inclined to be steady after 1500 epochs of forward training. The successful training of A_{net} informs that deep learning model could acquire the relationship between physical quantities. During the secondary training procedure, every layer in pre-trained forward model is frozen, that is, weights and bias of each node are not updated in layers of A_{net} but these values in B_{net} are optimized all the time. The cost function of this combination model can be expressed by $C_2 = \frac{1}{N} \sum |\mathbf{I}_{true} - A_{net}(\mathbf{S})|$. In a way, the “decoder” converts the multi-value problem into a single-value problem without complicated data filtering. As the corresponding relation between the design $\mathbf{S}$ and the response $\mathbf{I}$ changes, the training of connected network converges easily (nearly after 1500 epochs).

With the entire model trained successfully, the transient reactor for three-channel metasurfaces is completely constructed. When we take the middle layer as input and the last layer as the output, it could realize the forward data prediction. While we use the first layer as the input and the middle layer as the output, the desired structure parameters would be predicted by the middle layer, i.e., the output layer of inverse network, as long as we input the target power flow distribution.

TABLE I. Part of design results by deep learning model.

Target value	Theoretical value	Structural parameters(unit : mm)
[0.70, 0.00, 0.30]	[0.7006, 0.0026, 0.2967]	[9.01, 22.53, 10.75, 8.46, 7.79, 8.41, 8.40, 8.40]
[0.80, 0.00, 0.20]	[0.8005, 0.0007, 0.1988]	[8.71, 23.22, 11.32, 8.42, 7.62, 8.25, 8.21, 8.25]
[0.90, 0.10, 0.00]	[0.9000, 0.0996, 0.0004]	[8.06, 23.66, 14.06, 8.20, 6.40, 7.09, 7.70, 8.36]
[0.30, 0.30, 0.40]	[0.2989, 0.3007, 0.4004]	[11.80, 20.09, 11.07, 8.39, 7.93, 8.38, 8.47, 8.47]
[0.20, 0.30, 0.50]	[0.1990, 0.2999, 0.5011]	[12.78, 20.04, 10.39, 8.40, 7.92, 8.40, 8.49, 8.48]
[0.20, 0.50, 0.30]	[0.2000, 0.5005, 0.2995]	[12.83, 19.46, 11.79, 8.43, 7.56, 8.49, 8.49, 8.50]
[0.40, 0.20, 0.40]	[0.3998, 0.2005, 0.3997]	[11.06, 20.44, 11.04, 8.47, 8.22, 8.39, 8.49, 8.44]

151 Actually, what we are concerned more about is the function implemented by the latter, because
 152 nonlocal metasurfaces do not have a clear inverse theoretical relationship between structures and
 153 their responses, but the realization of the model allows this theoretical relationship to be simulated.
 154 Moreover, it avoids the troubles of conventional optimization methods that require to iterate many
 155 times to search for the best value and easily fall into local optimality.

156 **Nonlocal metasurfaces predicted by deep learning.** The target structures of acoustic metasur-
 157 faces could be predicted quickly and intelligently by the transient reactor. We randomly select
 158 several groups of power flow distributions with different ratios to verify the accuracy and effi-
 159 ciency of this reactor. Part of the prediction results is shown in Table I. The values on the left
 160 indicate the target ratios fed to the model and the theoretical values in middle represent the real
 161 energy distributions calculated by the predicted geometric parameters as shown in the right col-
 162 umn. All the ratios agree well with each other, which reveals the accuracy of this reactor.

For further verification, we choose three sets of predicted data for simulation and experiment. These three target ratios are set to be $\mathbf{I}_I = [1, 0, 0]$, $\mathbf{I}_{II} = [\frac{1}{2}, 0, \frac{1}{2}]$, $\mathbf{I}_{III} = [\frac{1}{3}, \frac{1}{3}, \frac{1}{3}]$. For these cases, the structures designed by the transient reactor are shown as follows (unit: mm):

$$\mathbf{S}_I = [6.80, 23.52, 11.74, 8.19, 6.41, 7.06, 8.09, 8.19],$$

$$\mathbf{S}_{II} = [10.10, 23.01, 10.12, 8.30, 7.99, 8.46, 8.37, 8.37],$$

$$\mathbf{S}_{III} = [11.53, 19.96, 11.53, 8.44, 7.80, 8.44, 8.46, 8.47].$$

163 Corresponding power flow ratios in theory are $\mathbf{I}'_I = [0.9910, 0.0026, 0.0063]$, $\mathbf{I}'_{II} = [0.4986,$
 164 $0.0017, 0.4998]$, $\mathbf{I}'_{III} = [0.3341, 0.3315, 0.3344]$, which fit well with the target values. The finite

FIG. 3. Intensity distribution in the total field. (a)-(c) Power flow value for S_I , S_{II} , and S_{III} along x direction at the surface of metasurface. The size and direction of white arrows in (d)-(f) respectively indicate the strength and direction of the power flow here.

165 element analysis is used here for numerical calculation, which could reveal intuitive sound field
 166 distribution based on various geometric sizes.

167 As shown in Fig. 1 and each matrix S , along with these rectangular pits, which are attached
 168 randomly in one period, comes the non-local effect from metasurfaces. Compared with traditional
 169 gradient metasurface, additional degree of freedom for sound regulation could be utilized in these
 170 metasurfaces, which supports the lateral transport of energy flow. To demonstrate more details
 171 of non-local coupling, the energy flow at $y = 0$ for these three metasurfaces in simulation has
 172 been extracted in Figs. 3a-c. The local intensity vector I_x could be obtained by $I_x = \frac{1}{2} \text{Re}[p(v_x)^*]$,
 173 where p means pressure and the v_x is the local velocity in the x direction. The sign of I_x/I_0
 174 refers to the direction of energy flow in x -axis. From Fig. 3a, I_x/I_0 are almost negative, which
 175 suggests the sound energy is concentrated and reflected in the left channel. In contrast, the curves
 176 in Figs. 3b-c float above and below zero, which indicates that the structures S_{II} , and S_{III} not
 177 only allocate energy to the left channel but also allocate to the others. Figs. 3d-f confirm this
 178 point more intuitively, corresponding to Figs. 3a-c, respectively, which reveal the strong lateral
 179 energy exchange between grooves. In any case, metasurfaces via non-local effects realize efficient
 180 wave manipulation by using lateral energy transport in the form of etched grooves. Although the

181 efficiency of non-local metasurfaces could be perfectly exerted in sound manipulation, the inverse
182 calculation is complicated due to the randomness of its geometrical parameters. Herein, deep
183 learning vastly simplifies it and facilitates the mass production for complex meta-structures. Not
184 only that, it enables designers without theoretical foundations to quickly implement on-demand
185 design.

186 **Experimental demonstrations.** When a plane wave fed perpendicularly into the metagratings,
187 scattering field with different ratios are represented in Figs. 4a-c, corresponding to $\mathbf{S}_I$ - $\mathbf{S}_{III}$ respec-
188 tively. The red arrows in the figure indicate the position and direction of the incident wave whilst
189 white arrows represent reflection. The reflected sound waves are obviously emitted from three
190 channels we set, which follow the target energy distribution.

191 The experimental samples with 20 periods are fabricated by 3D-printing technology using the
192 stereo lithography apparatus with photosensitive resin. Each measurement area is marked with a
193 red dashed frame in the upper panels of Figs. 4a-c and the size is $200 \times 200 \text{ mm}^2$. The experimental
194 results shown in the middle of Fig. 4 correspond to the scattering fields with target ratios ($\mathbf{I}_I$ - $\mathbf{I}_{III}$).
195 All the scattering fields in experiment have been normalized by the incident pressure. In addition,
196 we select a line in each measurement area and plot the data extracted from the line in lower
197 panels, defining $R(\theta) = \text{Re}(p_\theta/p_{\max})$ as the abscissa. Experimental results agree well with the
198 simulation, which demonstrates the fantastic functionality of the metasurfaces designed by deep
199 learning algorithm. In the last experimental field, the pressure field of the middle channel is weaker
200 than the two others, which may be caused by the multiple reflection between loudspeaker array
201 and the metasurface.

202 Discussion

203 In this work, we investigate the beam splitting function of the grooved metasurfaces based on
204 nonlocal coupling mechanism and realize the arbitrary regulation of the energy ratio for the multi-
205 channel metasurfaces. We successfully conducted model training on $\mathbf{S}$ and $\mathbf{I}$ taking into account
206 the nonlocality among subunits, so that finally the transient reactor can predict the target structures.
207 Meanwhile, the efficiency and accuracy of the network model are validated by simulations and
208 experiments. This intelligent method fairly shortens the optimization time for acoustic device
209 design and this way could be extended to other forms of device structures. Our work provides
210 new design solutions for non-local acoustic functional devices and promotes explorations of more
211 fancy properties of meta-materials. These results might inspire more combinations of acoustics and
212 artificial intelligence algorithms to assist in solving acoustic problems.

FIG. 4. Finite element simulation and experimental results for scattered pressure fields. (a)-(c) Scattered fields corresponding to S_I , S_{II} , S_{III} . The upper panels are the results of the simulation. To show the reflected fields more clearly, incident waves are not shown in the figures. Middle panels are experimental measurement fields, in which each measured area is a square with a size of $200 \times 200 \text{ mm}^2$. The insets in middle panels are 3D-printed sample photos (one period is shown). The values at black dashed lines in the middle panels are extracted and plotted in the lower panels, where the abscissa $R(\theta)$ is the ratio of the real part for p_θ and p_{max} . p_θ represents the pressure value at different positions on the black dotted lines.

Method

Neural network training mechanism. Given that one network model has D layers, then the first layer gets the input data X^0 and the layer D outputs the data X^D which has been activated many times by nonlinear activation functions. f represents the activation function. The complete neural network training process is mainly composed of two parts. In the former process, neural network parameters w and b are used to calculate the output values in conjunction with the activation function. Forward equations are as follows:

$$z^d = w^d X^{d-1} + b^d \quad \text{for } d = 1, 2, \dots, D, \quad (14)$$

$$X^d = f(z^d) \quad \text{for } d = 1, 2, \dots, D, \quad (15)$$

where z called weighted input will play an important role in the back propagation. Cost function(C) evaluates the error between predicted values and expected values. Actually, the goal of training given data is to seek suitable model parameters for which cost function return as small value as possible. Whereas this purpose depends on the later process to complete. In the back propagation, parameters w and b could be updated by gradient calculation and the global optimizer to improve the predictive performance of models. Referring to the back propagation algorithm proposed in Ref.⁵⁸, error gradient of each layer can be expressed as:

$$\delta^D = \frac{\partial C}{\partial X^D} f'(z^D), \quad (16)$$

$$\delta^d = \left[(w^{d+1})^T \delta^{d+1} \right] \odot f'(z^d) \quad for \quad d = 1, 2, \dots, D-1, \quad (17)$$

Then the partial differential of the cost function to the internal parameters of the network can be written as:

$$\frac{\partial C}{\partial w^d} = a^{d-1} \delta^d, \quad (18)$$

$$\frac{\partial C}{\partial b^d} = \delta^d. \quad (19)$$

Note that every neuron will go through these calculation cycles. Considering that the calculation relationship between two neurons located in adjacent layers is similar, for the sake of simplicity, we just use the superscript representing the number of layer for these parameters in above equations instead of marking the specific position of each neuron in a certain layer.

Network model structure and hyperparameter settings. In order to balance the training speed and prediction accuracy of the network model, we adopt the batch training method, that is, part of the data is sent for training each time. Batch size is the number of samples sent for each training. In all our training process, batch size is set to 256. We use the Leaky Relu as the activation function for each layer. The initial learning rates of forward training and tandem training are 0.0014 and 0.0006, respectively. The architecture of A_{net} is selected as 8-512-512-256-128-3 and B_{net} is 3-256-256-128-128-128-8. The 8 nodes match the number of structure parameters $\mathbf{S}$, and the 3 nodes correspond to the number of elements in the vector $\mathbf{I}$. Although pre-trained model and connected model could converge well after training over a thousand times, we terminated all the model training until epochs reached 5000 times to make the models more stable.

Finite element simulation. COMSOL MULTIPHYSICS is used as a preliminary verification tool for preliminary simulation verification of the predicted results. The pressure acoustic module

in the frequency domain is used to simulate the effect of the metasurface. A fixed-length plane incident wave as the sound source is incident on metasurfaces.

Experimental setup. The phase shift and amplitude of pressure fields are collected by a 1/8-inch microphone (Brüel & Kjær type 2670) and the data-acquisition hardware (NI PXI-4461 in NI PXIe-1071). The microphone as a probe scans fields in a step of 5mm. In the automatic scanning platform, we disposed 7 loudspeakers with a total width of 245 mm as the source. Samples are put in an organic glass plate waveguide about 2 cm high for experimental measurements. Foams are distributed at the edge of the measurement field to absorb external sound waves and reduce the influence of internal multiple reflection waves. We first measured the empty field with no sample placed, and then measured the total field with the placed sample. In this way, the difference between the two measurements is the result of the reflected field.

Data availability

The data that support the plots within this paper and other findings of this study are available from the corresponding author upon reasonable request.

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380 **Author contributions**

381 Y.L. conceived the idea. H.D. implemented model construction and training. X.F., and N.W.
382 provides support for basic physical model. H.D., B.J., and N.W. performed the experiments. Y.L.
383 and Q.C. supervised the whole project. H.D., X.F. and Y.L. wrote the paper with contribution from
384 all authors.

385 **Competing interests**

386 The authors declare no competing interests.