Deep learning assisted optical wavefront shaping in disordered medium

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ABSTRACT

Wavefront shaping (WFS) has been put forward several years ago to break the limitation caused by optical scattering in inhomogeneous medium, and realize optical focusing in disordered medium like biological tissues. However, usually, with traditional methods, WFS is time consuming and not cost efficient since it requires long time to obtain the information of the scattering medium. Here we propose the deep learning assisted wavefront shaping, which uses deep neural networks to predict the desired input optical modes that are needed to realize focusing after light passes through a scattering medium. Simulation results show that the pre-trained neural network is able to map output optical modes to input modes. Compared with previous methods which use iterative optimization, our method realizes a focused speckle pattern with the help of deep learning, which will definitely reduce complexity and time spent in optimization. Experiments will be conducted soon.

Keywords: wavefront shaping, deep learning, convolutional neural network, focusing

1. INTRODUCTION

When a coherent light beam passes through a disorder medium, strongly multiple scattering inside the medium can distort the wavefront, and interference from different scattering paths generates complex speckle patterns. Usually, light can only penetrate one mean free path (few hundred microns inside living tissues) [1] before the spatial coherence of light is totally lost. However, multiple scattering, which seems stochastic, is actually deterministic in nature [2], making refocusing light inside scattering medium possible. Wavefront shaping, controlling optical wavefront with the help of spatial light modulator (SLM), has been put forward several years ago to break the limitation on imaging resolution caused by light scattering in disordered medium, and realize tight optical focusing in strongly scattering medium like biological tissues.

The first wavefront shaping work was reported by Vellekoop and Mosk [3]. The most important principle of this experiment is that the transmitted electric field E_m in the CCD camera plane is a linear combination of the electric fields $E_n = A_n e^{i\phi_n}$ coming from the N different segments of the spatial light modulator (SLM), $E_m = \sum_{n=1}^{N} t_{mn} A_n e^{i\phi_n}$. Vellekoop and Mosk [3] obtained a focused, single speckle grain using an iterative optimization approach: the phases ϕ_n of each input electric field E_n corresponding to the n-th mode were cycled sequentially from 0 to 2π, and the phase values that maximized the intensity on a chosen pixel of the camera were recorded. After iteration of all input modes, the phases of all the input modes were set simultaneously to their recorded optimal value, resulting in a strong constructive interference at the chosen speckle grain as all the terms $t_{mn} A_n e^{i\phi_n}$ are in phase [3], effectively forming a very strong focus. The authors claimed that they enhanced the light intensity of a targeted speckle grain by a factor 1000 through a 10-mm thick layer of rutile (TiO2) [3].

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However, there is a drawback in Mosk' s method: if people want to focus light at different positions, the whole iterative optimization process has to be repeated multiple times, which is time-consuming. Therefore, after the initial demonstration of optical wavefront shaping by Vellekoop and Mosk, Popoff and his coworkers reported the measurement of an optical transmission matrix t_{mn} [4] in a strongly scattering layer for the first time. To do so, the transmitted speckle patterns were measured over the camera plane for a set of orthogonal input modes that form a full basis for all the possible SLM modes [5]. Since camera only recorded light intensity, interferences with a known wave front and a full field "four phases method" were used to obtain both the amplitude and phase information of transmitted speckle patterns [5]. Compared with the above reported iterative optimization method, one advantage of this transmission matrix approach is that one can directly get the amplitude and phase needed for input modes in order to obtain any desired output pattern without spending a lot of time conducting optimization.

Although recent publications demonstrated promising proof-of-concepts experiments, existing wavefront shaping methods take a long time to find the optimal input optical modes that can result in light focusing after a diffuser [3], and measurement of transmission matrix can be complicated. Deep learning is capable of discovering the complex relationship and has shown superior ability in facilitating biomedical imaging. It has been applied into MRI imaging [6], optical holography [7], photoacoustic tomography [8], etc. Here, we propose to apply deep neural networks into wavefront shaping, which can significantly reduce both computational complexity and time cost in optimization process, offering the potential to use this wavefront shaping method to achieve faster light focusing in disordered medium.

2. SIMULATION RESULTS

The forward and inverse processes of scattering are generally described as

$$y = H(x) \tag{1}$$

$$x = H^{-1}(y) \tag{2}$$

where $x \in R^{N_x}$ is the input optical modes, $y \in R^{Ny}$ is the speckle patterns measured through the scattering medium, $H(\bullet)$ is the forward scattering function, and $H^{-1}(\bullet)$ is the inverse scattering function. Here, Nx and Ny are the numbers of elements in the input and output modes, respectively. Since input optical modes are adjusted using SLM, x can be represented by SLM patterns. We directly calculate the inverse function $H^{-1}(\bullet)$, without the forward function $H(\bullet)$, based on neural network, where the relationship between a dependent variable (x) and an independent variable (y) is estimated by using a statistical model[9].

Usually, to control light and focus it, optimization starts with a totally random input mode, i.e., a random speckle pattern. Then different algorithms, such as genetic algorithm [10], are used to iteratively adjust the input modes that enter into a diffuser using SLM based on the feedback offered by optical speckle patterns [3] or photoacoustic signals [10]. Another drawback of existing algorithm such as genetic algorithm is that the optimized results can be easily stuck in local maximum/ minimum, indicating that there is no guarantee that the global maximum/ minimum value can be found using these algorithms. In order to solve the problems addressed above, here, we propose to apply deep learning into wavefront shaping, which can significantly reduce the time cost in optimization process, and converge to the global maximum/ minimum value.

Our method consists of two steps: First of all, SLM is applied to change input modes which will passes through a diffuser randomly, and a camera records their corresponding speckle patterns. A large amount of pairs of SLM patterns and speckle patterns are recorded, which serve as training samples of deep neural networks. Then a deep convolutional neural network (CNN) is constructed to approximate the inverse function $H^{-1}(\bullet)$. This task can be formulated as a supervised machine learning problem. Different scattered speckle patterns are regarded as inputs to the CNN, while the desired outputs are their corresponding SLM patterns. After training, the CNN can map speckle patterns collected to their corresponding SLM patterns accurately. By doing so, we can find the relationship between output speckle patterns and input SLM patterns with the help of CNN, eliminating the complex calculation process required by traditional methods. The second step is that if we send a desired, focused, single speckle pattern to the pre-trained network, the output SLM pattern predicted by CNN should result in good focusing after light passes through the same scattering medium. It is worth noting that the focal point in the speckle pattern can be at any position, and our CNN has the capability to find its corresponding SLM pattern.

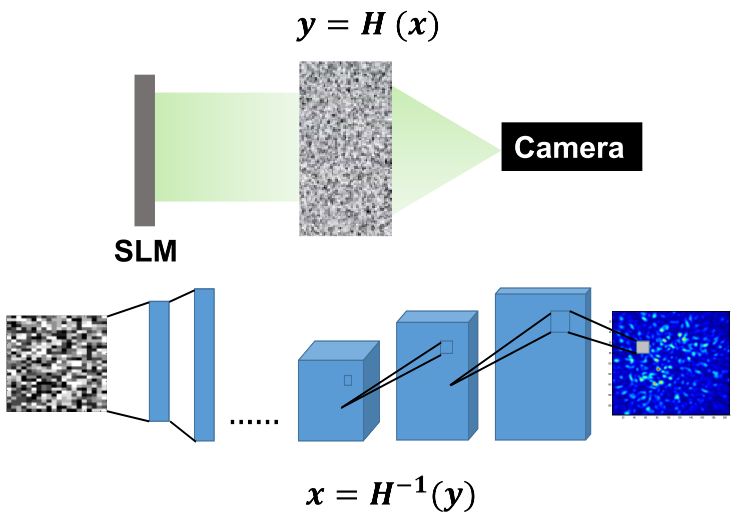
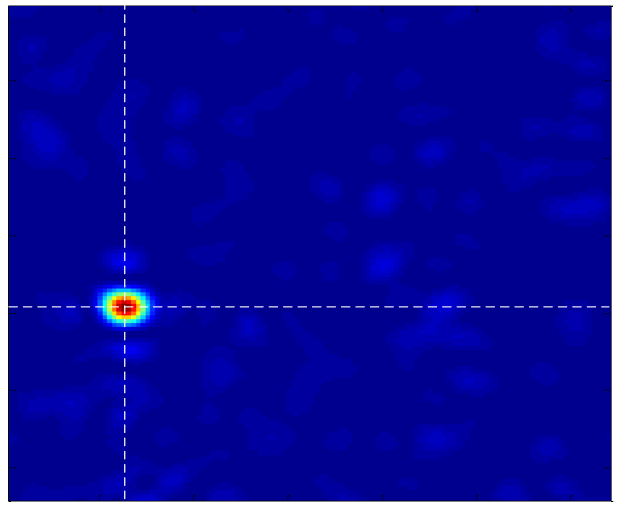
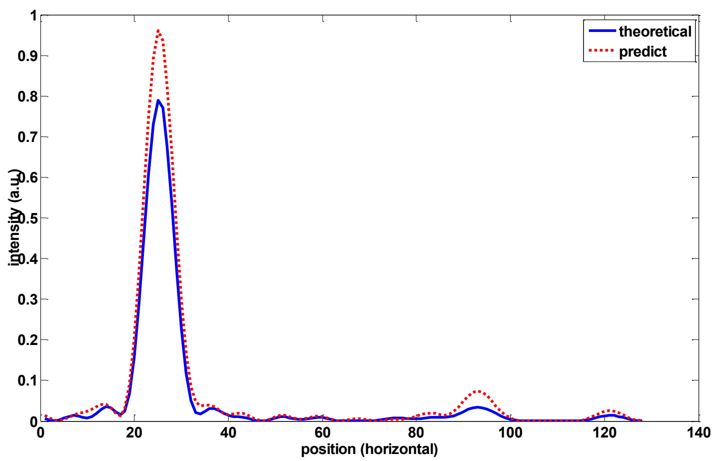


Figure 1. Illustration of wavefront shaping using neural networks. Light undergoes multiple scattering inside inhomogeneous media, and incident light with different SLM patterns results in different output speckle patterns. The speckle patterns serve as inputs to a pre-constructed convolutional neural network while the SLM patterns as the outputs. After proper training, convolutional neural networks are able to establish the relationship between the speckle patterns to their corresponding SLM patterns.

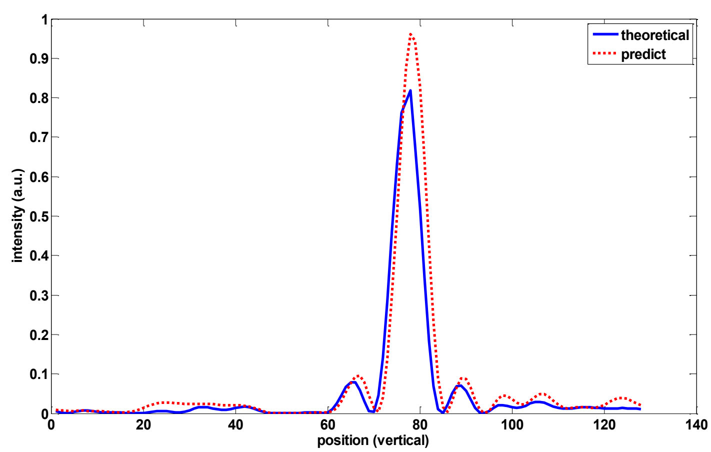
First of all, we present here the simulation results. As illustrated in Figure 1, a large amount of pairs of SLM and speckle patterns are used in training [11]. Speckle patterns serve as input to the neural network while SLM patterns serve as output. Simulation patterns are used in training first to validate the feasibility of this method. 10,000 pairs of speckle and SLM patterns are saved and used as training samples. The size of speckle patterns is 198 x 208, while the size of SLM patterns is 10 x 10. For each SLM pixel, it can modulate the phase of incoming optical mode continuously from 0 to 2π, and SLM patterns are scaled to 0-1. The constructed CNN consists of 6 convolutional layer with 32 (7 x 7), 48 (7 x 7), 64 (5 x 5), 72 (5 x 5), 96 (3 x 3), and 128 (3 x 3) filters respectively, followed by a fully connected layer with 0.5 dropout rate. 9,500 pairs of patterns are used to train the network, while the rest 500 pairs of samples are used for validation. Iterating 50 times spends nearly 30 minutes. We use the Keras library with the TensorFlow back-end for GPU-accelerated neural network training [11]. Our laptop has a NVIDIA GEFORCE GTX980 GPU. Loss is calculated using the default mean squared error function. After training, the validation loss is as low as 0.02, indicating that the difference between values predicted by the CNN and the target values is quite small. Phase difference between SLM patterns predicted by CNN and real SLM patterns is calculated pixel by pixel, and validation results show that the percentage of pixels whose phase difference is within π/2 is around 93%, indicating that 93% pixels contribute to the desired the speckle pattern that we want. After training, a randomly chosen focused single speckle pattern works as an input to the pre-trained CNN, and the predicted SLM pattern is sent to pass through the same scattering medium which is used to generate training samples. The output speckle pattern focuses to the same point pretty well, and it is almost the same as the focused pattern which is the input of the CNN, indicating that the CNN has already obtained the ability to describe the relationship between scattered speckle patterns and illumination SLM patterns. Once CNN has been trained, light control can be realized at one step, and iterative optimization is no longer needed. Results are shown in Figure 2. Figure 2 (a) and (d) are different focused speckle pattern obtained after light of the modes predicted by the CNN passes through the scattering system. Figure 2 (b) and (d) are light intensity profiles along horizontal direction of (a) and (d), and Figure 2 (c) and (f) are light intensity profiles along vertical direction of (a) and (d).



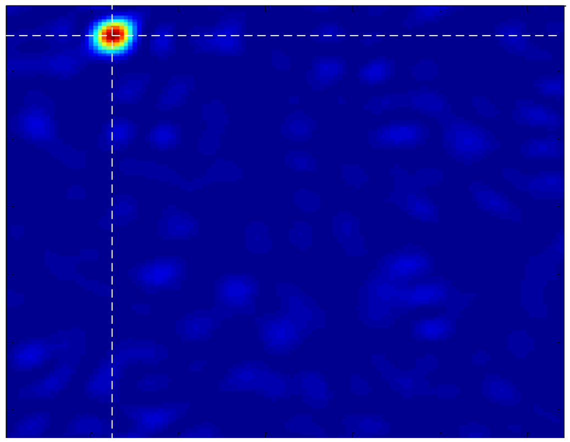
(a)


theoretical
predict
intensity (a.u.)
position (horizontal)

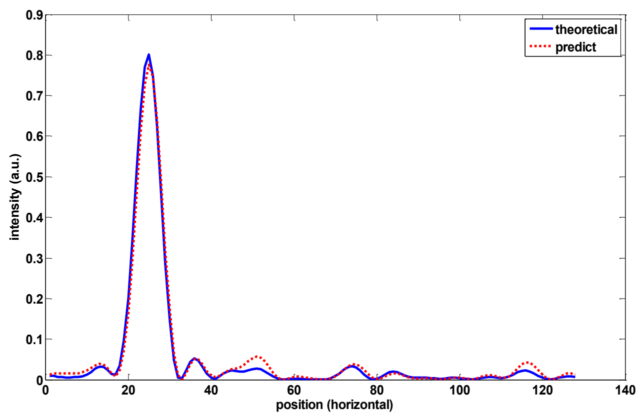
(b)


theoretical
predict
intensity (a.u.)
position (vertical)

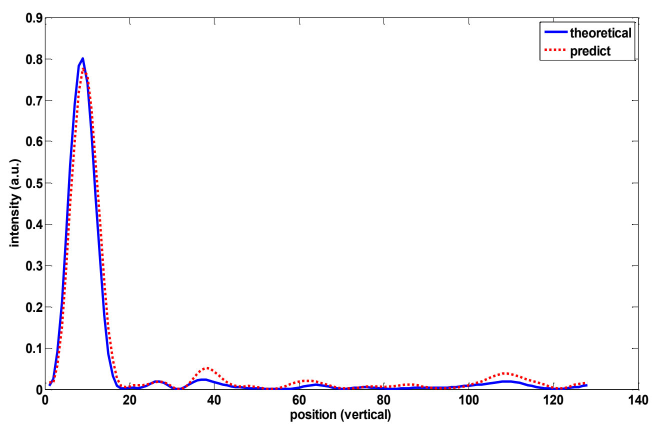
(c)



(d)



(e)



(f)

Figure 2. Focusing results with pre-trained CNN. (a) Simulation result of optical focusing. (b) Light intensity profile of (a) along horizontal direction through focal point. (c) Light intensity profile of (a) along vertical direction through focal point. (d) Simulation result of optical focusing at a position different from (a). (e) Light intensity profile of (d) along horizontal direction through focal point. (f) Light intensity profile of (d) along vertical direction through focal point.

3. CONCLUSION

Here we report the use of deep neural network to realize wavefront shaping and light focusing through scattering medium. Compared with previous wavaefront shaping methods that rely on iterative optimization or transmission matrix, our method realizes a focused, single speckle pattern with the help of deep neural network which is simpler and faster. Once our neural network has been trained, it is able to estimate the inverse scattering function inside a disordered medium, mapping output speckle patterns to input SLM patterns. In the future, experiments will be conducted soon.

REFERENCES

[1] Horstmeyer, Roarke, Haowen Ruan, and Changhuei Yang. "Guidestar-assisted wavefront-shaping methods for focusing light into biological tissue." Nature photonics 9.9 (2015): 563.

[2] Fernández, Jorge E., and Viviana Scot. "Deterministic and Monte Carlo codes for multiple scattering photon transport." Applied Radiation and Isotopes 70.3, 550-555. (2012).

[3] I. M. Vellekoop, and A. P. Mosk. “Focusing coherent light through opaque strongly scattering media.” Optics Letters, Vol.32, No.16, Aug. 2007.

[4] S. M. Popoff, G. Lerosey, et al. “Measuring the Transmission Matrix in Optics: An Approach to the Study and Control of Light Propagation in Disordered Media.” Physical Review Letters, 104, 100601, Mar. 2010.

[5] Bossy, Emmanuel, and Sylvain Gigan. "Photoacoustics with coherent light." Photoacoustics 4.1, 22-35. 248 (2016).

[6] Shah, Amit, et al. "Deeply learnt hashing forests for content based image retrieval in prostate MR images." Medical Imaging 2016: Image Processing. Vol. 9784. International Society for Optics and Photonics, (2016).

[7] Rivenson, Yair, et al. "Phase recovery and holographic image reconstruction using deep learning in neural networks." Light: Science & Applications 7.2 (2018): 17141.

[8] Antholzer, Stephan, Markus Haltmeier, and Johannes Schwab. "Deep learning for photoacoustic tomography from sparse data." arXiv preprint arXiv:1704.04587 (2017).

[9] Horisaki, Ryoichi, Ryosuke Takagi, and Jun Tanida. "Learning-based focusing through scattering media." Applied optics 56.15 (2017): 4358-4362.

[10] Lai, Puxiang, et al. "Photoacoustically guided wavefront shaping for enhanced optical focusing in scattering media." Nature photonics 9.2 (2015): 126.

[11] Turpin, Alex, Ivan Vishniakou, and Johannes d. Seelig. "Light scattering control in transmission and reflection with neural networks." Optics Express 26.23 (2018): 30911-30929.