Synchronous image reconstruction and depth information prediction through scattering media via multi-task network

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Abstract: Speckle signal is composed of a multitude of independently phased additive complex components. Because of scattering degradation, it is difficult to capture the object-related message. We present a novel deep learning method to reconstruct the object image and get depth information synchronously. The experimental result shows that our method can not only restore speckle patterns in a different position but also obtain over-rang object depth information accurately. Our method broadens the way to acquire multiple physical information about complex scattering conditions and accelerate the application of speckle in practice.

Keywords: speckle pattern; deep learning; image reconstruction; depth prediction.

To get object information through scattering media has broad application prospects in deep biological tissue analysis and harsh environment resolution [1, 2]. Due to diffusion, refraction, and absorption, the traditional calculation methods are unable to work under randomly scattering mode [3]. Some methods have been put forward to solve this problem, such as time-of-flight imaging [4], transmission matrix imaging [5, 6], and speckle auto-correlation method [7-9]. Almost all methods only solved the speckle image restoration and ignored other target information. To date, some methods can get the object depth via coherence gating [10], PSF manipulation [12], ME imaging windowed Fourier transforms [13] and chromatic aberration compensation [14]. This depth detection methods can only be applied within specific depth ranges and require complicated experimental facilities. Deep learning technique is a powerful means to solve complex mapping relationships through scattering media [15]. Instead of building a complex physical model, DL can generate an optimized model driven by a large-scale data and simplify the hardware requirements. DL has been successfully demonstrated to reconstruct a sample’s image and classify handwritten digits through scattering media [16-18]. Distance information describes the spatial position characteristics of the target, which is indispensable information for target positioning and accurate measurement. Unfortunately, the object depth information is ignored despite it plays an important role in practical applications.

Due to speckle patterns were captured from different positions, which results in more difficult reconstruction compared to a fixed position. Meanwhile, the depth information of the position should be predicted synchronously. In this letter, a novel DL method utilizing multi-task neural network is presented to reconstruct object image and detect depth information through scattering media synchronously. According to the characteristics of the speckle image and depth, we design a multi-task network containing two different attributes of the branch network and demonstrate our DL method. We have achieved different speckle patterns from multiple positions and trained our IDNet. Then, we can reconstruct unknown object images and predict depth information accurately via trained model.
The experimental setups for collecting the data for image reconstruction and depth of field acquisition are drawn schematically in figure 1. The incoherent light source in the experiment is a red LED with a central wavelength of 625 nm (M625L4, bandwidth: 17 nm, Thorlabs). We use a digital micromirror device (DMD) (DLC9500P24, pixel count: 1920 × 1080, pixel pitch: 10.8μm) to display the object images on its surface. In the process of collecting speckles, 1100 different handwritten digits are selected as object images from the MINIST database are sequentially displayed onto the DMD. We set a TIR prism to fold light path for capturing the patterns conveniently. We select the ground glass diffuser (Edmund, #83-416) as the scattering medium. A filter (FL632.8-1, Thorlabs) placed in front of sCMOS (pco.edge 5.5, resolution: 2560 × 2160, pixel size: 6.5 × 6.5) that allowed a well-defined wavelength band of light to transmit. Filter with LED as the system's narrow band incoherent light source. Lastly, the speckle patterns corresponding to different positions can be obtained by setting the horizontal stage.

An end-to-end IDNet is proposed to learn a statistical model relating to the speckle patterns generated by different positions. The content structure of IDNet shown in Fig.1. It is consists of two sub-networks to take on different tasks separately. The section of object image reconstruction follows the encoder-decoder architecture with modification of a long-range skip connection to improve reconstruction quality. The section of object depth prediction is consists of encoder part and fully connected layers. The input to the IDNet is a preprocessed 256*256 speckle pattern. Next, one input speckle pattern goes through two sub-networks synchronously, which produces restore image by image reconstruction sub-network and depth value by depth prediction sub-network.

The key structure of the multi-task network is based on Efficient Residual Factorized (ERF) layers proposed in ERFNet [19]. The ERF layers is a novel architecture design that leverages skip connections and one dimensional (1D) kernels convolutions. The skip connection is to build residual function. The 1D structure factorized convolution layers can reduce the computational costs compared traditional two dimensional (2D) residual block. The skip connection layers and 1D factorized convolution layers remain high efficiency and remarkable accuracy. Encoder part is composed of residual blocks and downsampling blocks. Encoder producing downsampled feature maps with more context to improve restore quality and reduce computation. The decoder part is
composed of upsampling blocks and deconvolution layers. The decoder producing upsampled feature maps to match the input resolution and deconvolution layers simplify computation requirements. In the section of object depth prediction, After obtaining the features about the depth of field information via encoder part, we use fully connected layers to get depth value.

In training the IDNet, we use the mean squared errors (MSE) loss function to evaluate the training model. The reconstruction and depth information prediction are is calculated as:

\[
Loss_I = \frac{1}{N} \sum_{i} \| I_i - \hat{I}_i \|^2
\]  
\[
Loss_D = \frac{1}{N} \sum_{i} \| D_i - \hat{D}_i \|^2
\]  
\[
Loss = Loss_I + Loss_D
\]  

Where \( I_i \) and \( \hat{I}_i \) are the reconstructed images and ground truth, \( D_i \) and \( \hat{D}_i \) are depth predicted value and actual value, respectively; \( i \) is the number of the training dataset, and \( N \) is the mini-batch size. We choose the sum of the reconstruction loss and depth prediction loss as our back-propagated loss through the IDNet.

For training IDNet, we choose 1 k speckle patterns as training data each positions, 50 speckle patterns as validation data, and 50 speckle patterns as testing data. The training sets were processed in 16 image batches. Each IDNet is trained with 200 epochs by Adam optimizer for up to 48 hours. The learning rate of \( 5 \times 10^{-4} \) is used for the first 100 epochs, and \( 2.5 \times 10^{-4} \) is used for the final 100 epochs. We use a computer with a Linux-Ubuntu 16.04 operating system. The IDNet were performed using the PyTorch 1.2.0 Python library on a singe NVIDIA GeForce RTX 2080Ti graphics unit.

For describing the feasibility of multi-task network, we set different quantity of positions to capture speckle patterns. From the Fig.3, the reconstruction results and depth predictions are presented with object ground truth and actual position. For evaluating the reconstruction performance and depth prediction accuracy quantitatively, the average peak signal-to-noise ratio (PSNR), mean structural similarity (SSIM), and depth average error are calculated and shown in Table 1. The definition of PSNR is:

\[
PSNR = 10 \times \log_{10} \frac{255^2}{MSE}
\]  

The definition of SSIM value between image 1 and image 2 is:

\[
SSIM = \frac{(2\mu_1\mu_2+c_1)(2\sigma_{1,2}+c_2)}{(\mu_1^2+\mu_2^2+c_1)(\sigma_1^2+\sigma_2^2+c_2)}
\]  

Where \( \mu_1 \) and \( \mu_2 \) are their means, \( \sigma_{1,2} \) is the covariance of two images, \( \sigma_1^2 \) and \( \sigma_2^2 \) are the variances, \( c_1 \) and \( c_2 \) are regularization parameters [20].
To summarize, in this letter, we propose an end-to-end IDNet specially designed for simultaneous reconstruction of object image and prediction of depth information from a single digital speckle pattern. This new method obtains reliable object image reconstruction and depth information, with PSNR about 34.95 dB for reconstruction and average error about $1.086 \times 10^{-2}$ mm for depth prediction. It is proved that the DL method can not only recover the speckle image information but also predict the object depth information behind the scattering media accurately. Our work provides an idea for the next step to measure the object space position, the geometric size, and other physical information.

$^\dagger$These authors contributed equally to this work.

REFERENCES
1. Ntziachristos, Vasilis. "Going deeper than microscopy: the optical imaging frontier in biology." Nature methods 7.8, 603 (2010).
2. Gibson, A. P., J. C. Hebden, and Simon R. Arridge. "Recent advances in diffuse optical imaging." Physics in Medicine & Biology 50.4, R1 (2005).
3. M. Lyu, H. Wang, G. Li, and G. Situ, "Exploit imaging through opaque wall via deep learning," arXiv preprint, arXiv:1708.07881 (2017).
4. Velten, Andreas, et al. "Recovering three-dimensional shape around a corner using ultrafast time-of-flight imaging." Nature communications 3, 745 (2012).
5. S. Popoff, G. Lerosey, R. Carminati, M. Fink, A. Boccara, and S. Gigan, “Measuring the transmission matrix in optics: an approach to the study and control of light propagation in disordered media,” Phys. Rev. Lett. 104, 100601 (2010).
6. A. Drémeau, A. Liutkus, D. Martina, O. Katz, C. Schülke, F. Krzakala, S. Gigan, and L. Daudet, “Reference-less measurement of the transmission matrix of a highly scattering material using a DMD and phase retrieval techniques,” Opt. Express 23, 11898–11911 (2015).
7. J. Bertolotti, E. G. van Putten, C. Blum, A. Lagendijk, W. L. Vos, and A. P. Mosk, “Non-invasive imaging through opaque scattering layers,” Nature 491, 232–234 (2012).
8. O. Katz, P. Heidmann, M. Fink, and S. Gigan, “Non-invasive single-shot imaging through scattering layers and around corners via
speckle correlations,” Nat. Photonics 8, 784–790 (2014).

9. A. Porat, E. R. Andresen, H. Rigneault, D. Oron, S. Gigan, and O. Katz, “Widefield lensless imaging through a fiber bundle via speckle correlations,” Opt. Express 24, 16835–16855 (2016).

10. Guy Indebetouw and Prapong Klyubun, "Imaging through scattering media with depth resolution by use of low-coherence gating in spatiotemporal digital holography," Opt. Lett. 25, 212-214 (2000).

11. Xie, Xiangsheng, et al. "Extended depth-resolved imaging through a thin scattering medium with PSF manipulation." Scientific reports 8.1, 4585 (2018).

12. Kevin T. Takasaki and Jason W. Fleischer, "Phase-space measurement for depth-resolved memory-effect imaging," Opt. Express 22, 31426-31433 (2014).

13. Xie, Junpeng, et al. "Depth detection capability and ultra-large depth of field in imaging through a thin scattering layer." Journal of Optics (2019).

14. LeCun, Yann, Yoshua Bengio, and Geoffrey Hinton. "Deep learning." nature 521.7553, 436 (2015).

15. Yunzhe Li, Yujia Xue, and Lei Tian, "Deep speckle correlation: a deep learning approach toward scalable imaging through scattering media," Optica 5, 1181-1190 (2018).

16. Yiwei Sun, Jianhong Shi, Lei Sun, Jianping Fan, and Guihua Zeng, "Image reconstruction through dynamic scattering media based on deep learning," Opt. Express 27, 16032-16046 (2019).

17. Navid Borhani, Eirini Kakkava, Christophe Moser, and Demetri Psaltis, "Learning to see through multimode fibers," Optica 5, 960-966 (2018).

18. Romera, Eduardo , et al. "ERFNet: Efficient Residual Factorized ConvNet for Real-Time Semantic Segmentation." IEEE Transactions on Intelligent Transportation Systems 19.1, 263-272 (2018).

19. Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, IEEE Trans. Image Process 13, 600 (2004).