Frontiers in Optics + Laser Science (FiO/LS) @ Optica Publishing Group 2022

Adaptive volumetric descattering in digital holography

Hao Wang[1], Waleed Tahir[1], and Lei Tian[1, 2, *]

1 Department of Electrical and Computer Engineering, Boston University, Boston, MA 02215, USA

2 Department of Biomedical Engineering, Boston University, Boston, MA 02215, USA.

leitian@bu.edu

Abstract: We demonstrate an adaptive learning framework, termed dynamic synthesis network (DSN), which dynamically synthesizes model weights and adapts to different scattering conditions. The efficiency of DSN is demonstrated in holographic 3D particle descattering.

1. Introduction

Deep learning-based descattering has been broadly investigated in recent years. A typical framework is to train an "expert" network under a specific scattering condition. However, the expert's performance sharply degrades when the testing condition differs from the training. An alternative brute-force approach is to train a "generalist" network with diverse images captured under different scattering conditions. Unfortunately, it generally requires a larger network to learn the diversity and a sufficiently large training set to avoid overfitting. Here, we demonstrated an adaptive learning framework, termed dynamic synthesis network (DSN), which dynamically synthesizes the model weights for different scattering conditions [1]. The adaptability is achieved by a novel "mixture of experts" architecture that enables dynamically synthesizing a network by mixing multiple experts using a gating network, which encodes the scattering image to provide the synthesis weights for each expert network. We demonstrate our DSN in holographic 3D particle imaging for a variety of scattering conditions, where the DSN is entirely trained on the simulated dataset and can be generalized to experiments smoothly. We expect our dynamic synthesis concept can be widely used in different imaging processing areas such as image denoising, etc.

2. Method

We demonstrate the efficiency of our DSN framework to perform descattering on holographic particle 3D reconstruction.

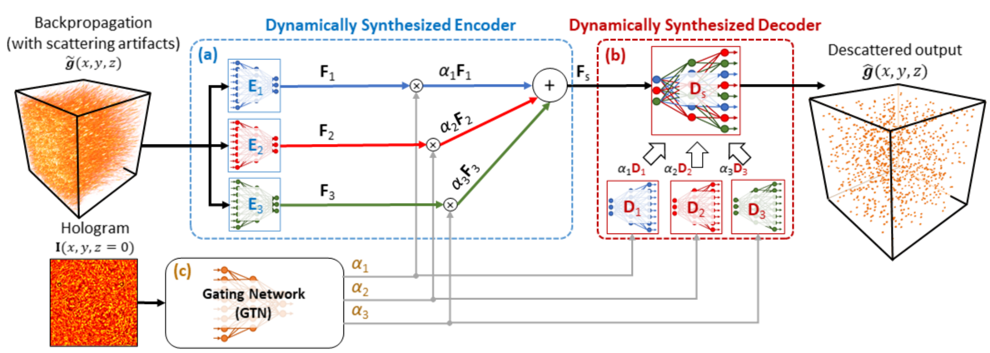

Figure 1: **Dynamic synthesis network (DSN) framework.** The DSN combines multiple DNNs for adaptively removing scattering artifacts in the input. (a) In the first stage, the expert encoders $\mathrm{E_i}$ ($i \in \{1,2,3\}$) extract a diverse set of multi-scale spatial features from the holographically backpropagated input volume $\tilde{\mathbf{g}}$. The extracted multi-scale feature maps from each encoder are labeled as $\mathbf{F_i}$. To adaptively process an input with an arbitrary scattering condition, a dynamically synthesized feature map $\mathbf{F_s}$ is computed as a weighted sum of the expert feature maps: $\mathbf{F_s} = \sum_{i=1}^{3} \alpha_i \mathbf{F_i}$. The synthesized feature $\mathbf{F_s}$ is fed into a dynamically synthesized decoder D_s to produce the descattered output $\hat{\mathbf{g}}$. (b) Different from the encoder, the decoder $\mathrm{D_s}$ is computed as a weighted sum of the expert decoders' network parameters: $\mathrm{D_s} = \sum_{i=1}^{3} \alpha_i \mathrm{D_i}$. (c) The gating network provides the adapting mechanism by predicting the synthesis weights α_i based on the matching hologram input.

The schematics of our DSN framework are shown in Fig. 1. The input to the network is the preprocessed scattering-contaminated 3D volume estimated from the scattering image. The network is then trained to remove scattering artifacts within the 3D volume, which is highly related to the scatterer density, size, refractive index contrast, and further complicated by the depth-varying characteristics throughout the whole volume. To reconstruct particles embedded within the scattering artifacts, the expert encoder first independently extracts a set of multi-scale spatial feature maps from the input volume, which acts as the “basis” of synthesized feature representation. Since each expert encoder has different “specializations”, the combined set of feature maps provides a diverse representation of the scattering volume. To optimally synthesize these multi-scale features for a specific scattering condition, a linearly weighted sum of the extracted feature maps is computed using the “synthesis weights” given by the gating network (see Fig. 1(a)). On the decoding end, the DSN dynamically synthesizes the decoder by mixing a set of expert decoders. This process is performed by directly computing a linearly weighted sum of the network weights of the expert decoders (see Fig. 1(b)). Finally, the synthesized features from the encoder are decoded by the synthesized decoder to produce the descattered output volume. To train our DSN, we use beam-propagation method (BPM) [2] to accurately generate holograms and the backpropagation method to roughly estimate the scattering-contaminated 3D volume from generated holograms. Then the generated holograms, 3D volumes, and ground truth particles are used as input and output to train our network. After finishing training, our network can be used for experimental captured scattering images and have state-of-the-art descattering performance for a wide range of scattering conditions.

3. Result and Conclusion

We quantitatively evaluate the DSN performance by comparing the reconstructed and the ground-truth particle locations using the Jaccard Index (JI) similarity score across the depths. As shown in Fig. 2, the DSN generally provides better reconstruction within a broad range of scattering conditions than both the generalist and the matching expert, in particular for high densities (ρ ≥ 6.41 × 104 particles/μL) cases.

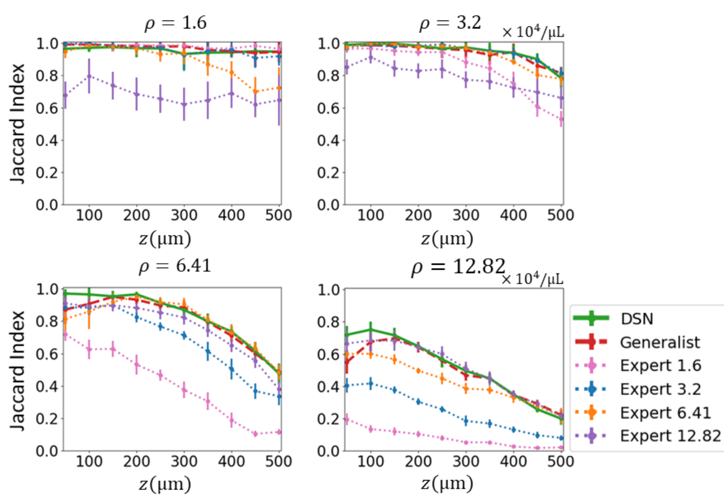

Figure 2: **Quantitative performance evaluation.** Particle localization performance is quantitatively compared between the DSN, the generalist, and the expert DNNs using JI. Each plot indicates the results on a test data set at the density labeled above each plot and with particle diameter 1.0 μm and refractive index contrast 0.26. “Expert ρ” represents the expert DNN trained on the data set with the density ρ (×10^4 particles/μL).

In conclusion, we have presented and experimentally demonstrated a novel *adaptive* deep learning framework. We demonstrated our network’s generalization capability of adaptively removing 3D scattering artifacts and achieving state-of-the-art performance for a wide range of scattering conditions.

4. References

[1] W. Tahir, H. Wang, and L. Tian, “Adaptive 3D descattering with a dynamic synthesis network,” Light: Science & Applications, vol. 11, no. 42, 2022.

[2] H. Wang, W. Tahir, J. Zhu, and L. Tian, “Large-scale holographic particle 3d imaging with the beam propagation model,” Optics Express, vol. 29, no. 11, pp. 17159–17172, 2021.