Invited Paper

Learning Plane-to-Multiplane Light Propagation improves Hologram Optimization

Chuanjun Zheng[a], Yicheng Zhan[a], and Kaan Akşit[a]

[a]University College London

ABSTRACT

Computer-Generated Holography (CGH) reconstructs Three-Dimensional (3D) scene by encoding information into holograms. Traditional CGH algorithms decompose the 3D scenes into multiple planes at different depth levels and simulate light propagation between these planes. However, conventional light propagation methods used in CGH are limited to plane-to-plane simulations, which may increase computational demands when a 3D scene is represented with numerous successive planes. We introduce a novel learned model that simulates light propagation from a single hologram plane to multiple planes in a single forward pass. In this way, our method can help reduce the computational complexity of optimizing 3D holograms in CGH algorithms.

Keywords: Computational-Generated Holography, Light Propagation, Convolutional Neural Networks

1. INTRODUCTION

CGH algorithms often represent 3D scenes as a series of planes at different depth levels.[1,2] Conventional light simulation methods, such as the Angular Spectrum Method (ASM),[3] are typically used for light propagation between these planes in both learning-based[4,5] and optimization-based[2] CGH methods. Recently, learning-based light propagation models have been introduced to bridge the gap between physical accuracy and computational simulation. These models may incorporate camera-in-the-loop strategies[4] or learn a large kernel in the frequency domain.[6] However, those light propagation techniques in CGH remain limited to plane-to-plane simulations. When a 3D scene is represented by multiple planes, this method requires separate computations for each plane, resulting in increased computational costs. In this work, we propose a learned plane-to-multiplane light propagation model that enables light propagation from a plane to multiple target planes in a single forward pass. Our approach utilizes a U-Net architecture,[7] enhanced with a global feature module[8] to mitigate artifacts and capture global information. This method significantly reduces the computational complexity of optimizing 3D holograms in CGH algorithms, offering a more efficient solution for light propagation in 3D scenes.

2. LEARNING PLANE-TO-MULTIPLANE LIGHT PROPAGATION MODEL

We adopt a U-Net architecture[7] as the foundation for our light propagation model. The input to the network consists of a hologram combined with a series of distance values. These distance values are transformed into distance maps, where each map has the same dimensions as the hologram, with all pixels sharing the same distance value. The hologram and the distance maps are concatenated, forming the input to the network. The model generates a series of images at different depth planes as its output.

The model processes the input through an initial convolutional layer, which extracts features from both the hologram and distance maps. The U-Net structure comprises three encoder layers and three decoder layers with skip connections that link corresponding encoder and decoder layers. Each encoder layer consists of three convolutional layers that progressively extract features at different scales, while each decoder layer contains a transposed convolution followed by two standard convolutions. The encoder and decoder are connected by the global feature module inspired by RSGUNet.[8] It collects global context and mitigates potential local artifacts

Further author information: (Send correspondence to Kaan Akşit and Chuanjun Zheng)
Kaan Akşit: Email: k.aksit@ucl.ac.uk; Chuanjun Zheng: Email: chuanjunzhengcs@gmail.com

Practical Holography XXXIX: Displays, Materials, and Applications, edited by
Pierre-Alexandre J. Blanche, Hiroshi Yoshikawa, Proc. of SPIE Vol. 13390,
1339006 · © 2025 SPIE · 0277-786X · doi: 10.1117/12.3040869

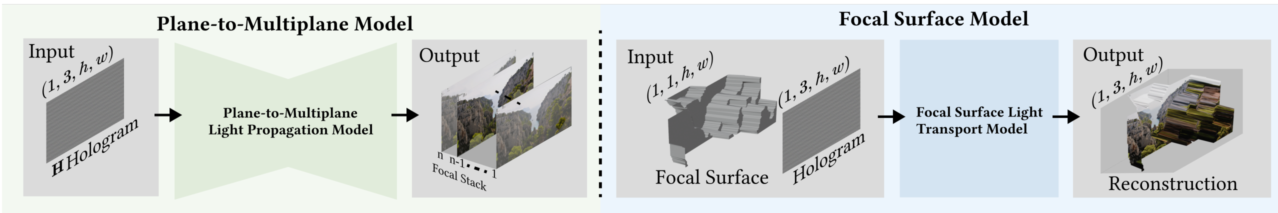

Figure 1. Left: Plane-to-multiplane light propagation model presented in this paper; Right: Our enhanced focal surface holographic light transport model.[9]

during decoding. The module applies two convolutional layers followed by an average pooling layer, and compressing the spatial information into a global feature vector. These global features are then processed through linear layers to mitigate artifacts. This model was developed with the support of Odak.[10]

More recently, we have proposed a more advanced light propagation model known as the focal surface holographic light transport[9] for hologram optimization. Instead of simulating plane-to-plane light propagation, we replace the target planes with a focal surface and propagate light from a plane to the target surface in a single inference, which is achieved by spatially varying convolution.[11,12] This approach simplifies hologram verification and calculation for holographic displays. This new approach improves the simulation speed by 10x and accelerates the hologram optimization process by 1.5x.

REFERENCES

[1] Kavaklı, K., Itoh, Y., Urey, H., and Akşit, K., "Realistic defocus blur for multiplane computer-generated holography," in [*2023 IEEE Conference Virtual Reality and 3D User Interfaces (VR)*], 418–426, IEEE (2023).

[2] Kavaklı, K., Shi, L., Urey, H., Matusik, W., and Akşit, K., "Multi-color holograms improve brightness in holographic displays," in [*SIGGRAPH Asia 2023 Conference Papers*], 1–11 (2023).

[3] Matsushima, K. and Shimobaba, T., "Band-limited angular spectrum method for numerical simulation of free-space propagation in far and near fields," *Optics express* **17**(22), 19662–19673 (2009).

[4] Choi, S., Gopakumar, M., Peng, Y., Kim, J., and Wetzstein, G., "Neural 3d holography: Learning accurate wave propagation models for 3d holographic virtual and augmented reality displays," *ACM Transactions on Graphics (TOG)* **40**(6), 1–12 (2021).

[5] Shi, L., Li, B., and Matusik, W., "End-to-end learning of 3d phase-only holograms for holographic display," *Light: Science & Applications* **11**(1), 247 (2022).

[6] Kavaklı, K., Urey, H., and Akşit, K., "Learned holographic light transport," *Applied Optics* **61**(5), B50–B55 (2022).

[7] Ronneberger, O., Fischer, P., and Brox, T., "U-net: Convolutional networks for biomedical image segmentation," in [*Medical image computing and computer-assisted intervention–MICCAI 2015: 18th international conference, Munich, Germany, October 5-9, 2015, proceedings, part III 18*], 234–241, Springer (2015).

[8] Huang, J., Zhu, P., Geng, M., Ran, J., Zhou, X., Xing, C., Wan, P., and Ji, X., "Range scaling global u-net for perceptual image enhancement on mobile devices," in [*Proceedings of the European conference on computer vision (ECCV) workshops*], 0–0 (2018).

[9] Zheng, C., Zhan, Y., Shi, L., Cakmakci, O., and Akşit, K., "Focal surface holographic light transport using learned spatially adaptive convolutions," in [*SIGGRAPH Asia 2024 Technical Communications (SA Technical Communications '24)*], *SA '24* (Dec. 2024).

[10] Akşit, K., Beyazian, J., Chakravarthula, P., Chen, Z., Doğan, M. D., Güzel, A. H., Itoh, Y., Kam, H., Karadeniz, A. S., Kavaklı, K., Shi, L., Spjut, J., Walton, D. R., Wu, J., Yılmaz, D., Yujie, W., Zhu, R., Xie, W., and Zhan, Y., "Odak," (Oct. 2024).

[11] Zheng, C., Shi, D., and Liu, Y., "Windowing decomposition convolutional neural network for image enhancement," in [*Proceedings of the 29th ACM International Conference on Multimedia*], 424–432 (2021).

[12] Xu, C., Wu, B., Wang, Z., Zhan, W., Vajda, P., Keutzer, K., and Tomizuka, M., "Squeezesegv3: Spatially-adaptive convolution for efficient point-cloud segmentation," in [*Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part XXVIII 16*], 1–19, Springer (2020).