Focal Surface Holographic Light Transport using Learned Spatially Adaptive Convolutions

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Fig. 1. Based on previous works [Kavaklı et al. 2023a], we optimize the hologram given an image and its corresponding depth map. The hologram is reconstructed on six depth planes using ASM. Subsequently, we generate the focal surface by randomly assigning different depth values to the in-focus regions. In the in-focus restoration module, we segment the 3D reconstructions based on focal surfaces and merge them into a target image, with a mask indicating the focused areas. (Source image: Tobi 87, Link: Wikimedia Commons)

1 DATASET GENERATION

We start with an RGB image and its corresponding depth map to optimize the hologram H, following methods from previous work [Kavaklı et al. 2023a]. The optimization is carried out with two different propagation distances (0mm and 10mm) at the resolution 1920×1080 . For both cases, we reduce the iteration counts to introduce noise into the hologram, which is beneficial for the model to learn the high-frequency information. The optimized hologram is then propagated onto six distinct depth planes, producing six reconstructions. Next, we generate the focal surface D by randomly assigning different depth values to the focused regions on these six depth planes. These depth values are selected from a uniform distribution representing six distinct depth values. As shown in Fig. 1, the focal surface is then processed by the In-focus Restoration module, which we extract the focused and defocused regions from the 3D reconstructions and combine them into a single target image R with the corresponding mask M. For the dataset, we use 300 RGB images as the training set and another 100 images for the test set. For each RGB image, we generate five arbitrary focal surfaces, resulting in 1500 training cases and 500 testing cases.

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2 DISPLAY PROTOTYPE



Fig. 2. An image of our holographic display prototype

We build an on-axis holographic display prototype using a phase-only Spatial Light Modulator (SLM) with Fisba ReadyBeam Lasers (420, 520, and 638 nm). The SLM is a Jasper Display SLM Research kit (2400 by 4094 pixels and 3.74µm pixel pitch). We brought optical components from Thorlabs to augment our holographic display prototype.



Fig. 3. Visual comparison on simulations between ASM 6 and Ours 6 at six depth planes under 0 mm and 10 mm propagation distances. (Source image: Martin Kníže, Link: Wikimedia Commons)



Ours 6

ASM 6

Fig. 4. Comparing experimental captures of ASM 6 and Ours 6 under 0 mm propagation distance. (Source image: Martin Kníže, Link: Wikimedia Commons)