Content-adaptive targeting scheme for holographic displays

SPIE.

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PROBLEM DESCRIPTION

Holographic displays use spatial light modulators (SLMs) to generate 3D images through complex wave field modulation. While conventional methods use multiplane focal stacks as ground truth for Computer-Generated Holography (CGH) optimization, they face several challenges. Recent works[1,2] have improved image quality and blur rendering but often struggle with depth-dependent effects and computational efficiency. A key overlooked issue is the slicing artifacts from axial propagation, particularly noticeable at depth discontinuities due to correlated axial intensities, see Fig. 2.

Fig. 1 The slabs generated by slicing the RGB image.

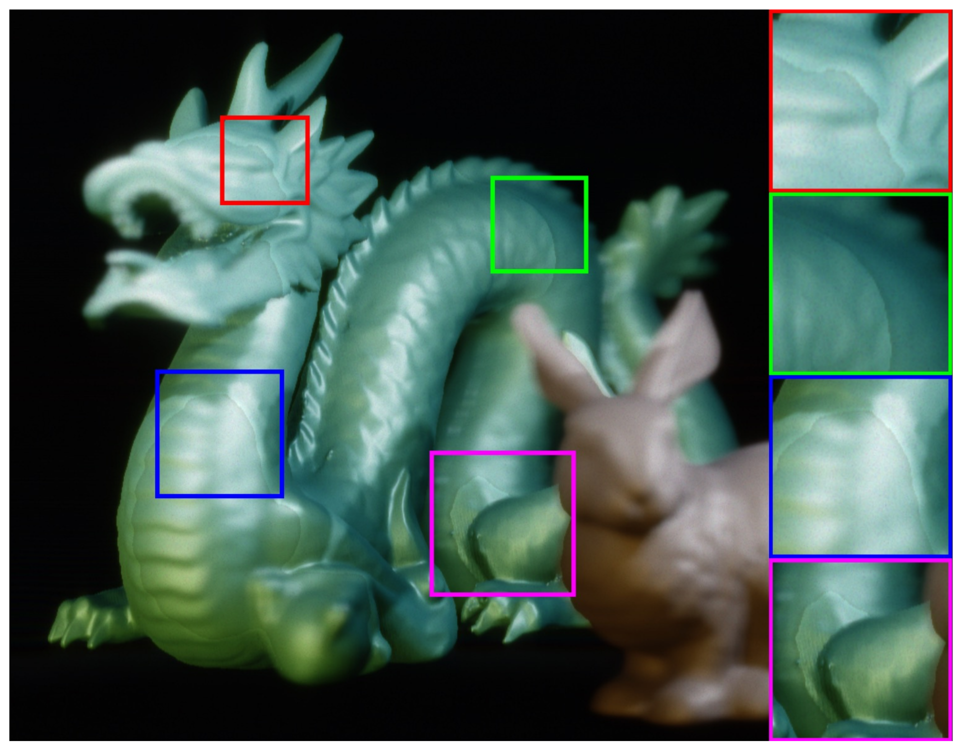

Fig. 2 Slicing artifacts in the reconstructed images by the CGH pipeline.

In this work, we propose a new focal stack targeting scheme for CGH acquisition that considers the axial holographic projection and detours the depth-slicing problem by leveraging the human visual perception factors. The simulated results maintain the image qualities at the salient areas while reducing the slicing artifact.

METHODS

Our method regularizes contrast and slicing boundaries in the process of generating a focal stack by solving the following minimization problem:

$$\hat{d} \leftarrow \arg\min_{d} \left(\underbrace{-\lambda_1 \log(\mathrm{C}(\mathsf{F}))}_{\text{Contrast Loss}} + \lambda_2 \underbrace{\sum_{i=1}^{N} |\mathcal{S}(\mathsf{F}_i)| * |\mathcal{S}(\mathsf{F}_{i+1})| * \mathfrak{s}(I)}_{\text{Slicing Boundaries Loss}} \right),$$

where, $d \in \mathbb{R}^{1\times N}$ denotes the depth plane distribution of the focal stack $\mathsf{F} \in \mathbb{R}^{N\times H\times W}$. $C(\mathsf{F})$ denotes our formulated contrast calculation, $\mathcal{S}$ denotes the Sobel edge detector, and $\mathfrak{S}$ is the saliency predictor for the RGB image I.

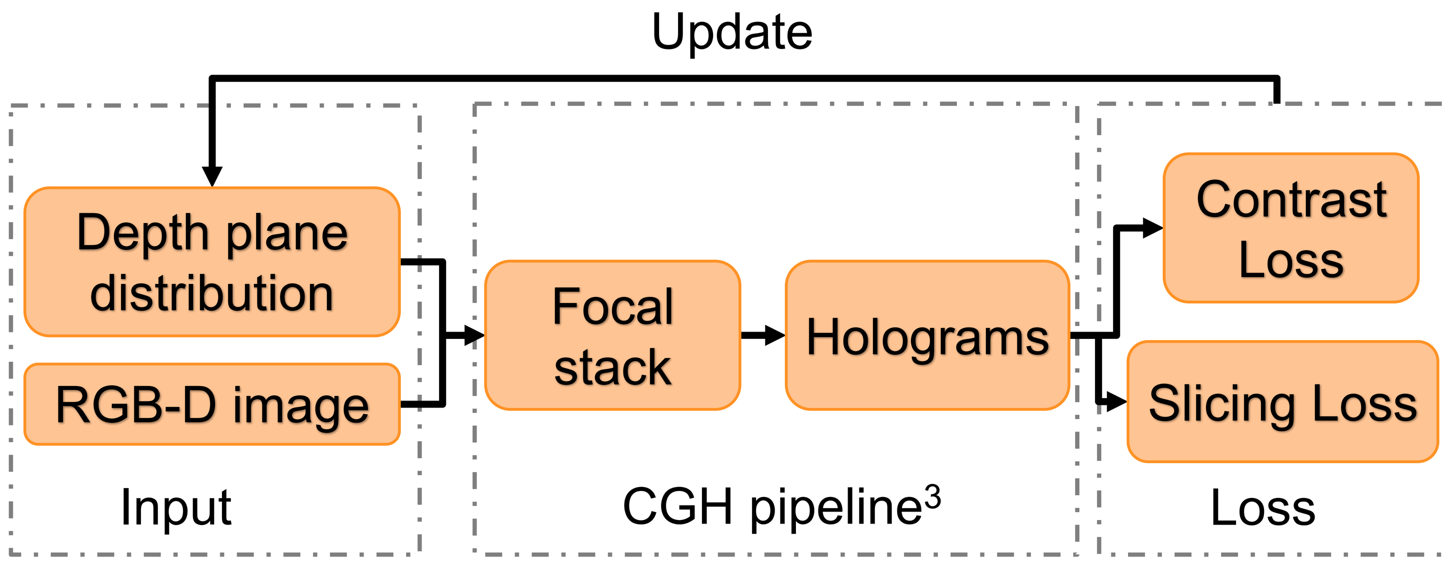

Fig. 3 The overview of the optimization for the targeting scheme.

For the perceived contrast estimation, a focal stack is decomposed into multiple levels of Laplacian and Gaussian pyramids. The contrast level defined by each spatial frequency band is defined by the ratio between the Laplacian pyramid and the bilinearly upsampled Gaussian in the next pyramid level. Then, the contrast sensitivity is multiplied per spatial frequency band to map the physical contrast to the perceived contrast domain. Thus, the overall perceived contrast of a focal stack can be calculated by the function[4]:

$$C(\mathsf{F}) = \frac{1}{L} \sum_{I_f \in \mathsf{F}}^{N} \sum_{l=1}^{L} \frac{\mathfrak{L}_l(I_f)}{\mathcal{U}(\mathcal{G}_{l+1}(I_f))} * \mathbf{s}_l,$$

where, the L is the number of pyramid levels, (8 in our experiment), and $\mathcal{U}$ is the upsampling operator. $\mathfrak{L}_l$ is the Laplacian pyramid, $\mathcal{G}_l$ is the Gaussian pyramid, and $\mathbf{s}_l$ is the contrast sensitivity corresponding to the l-th spatial frequency band. We employed Barten's contrast sensitivity model[5] for the contrast sensitivity.

RESULTS

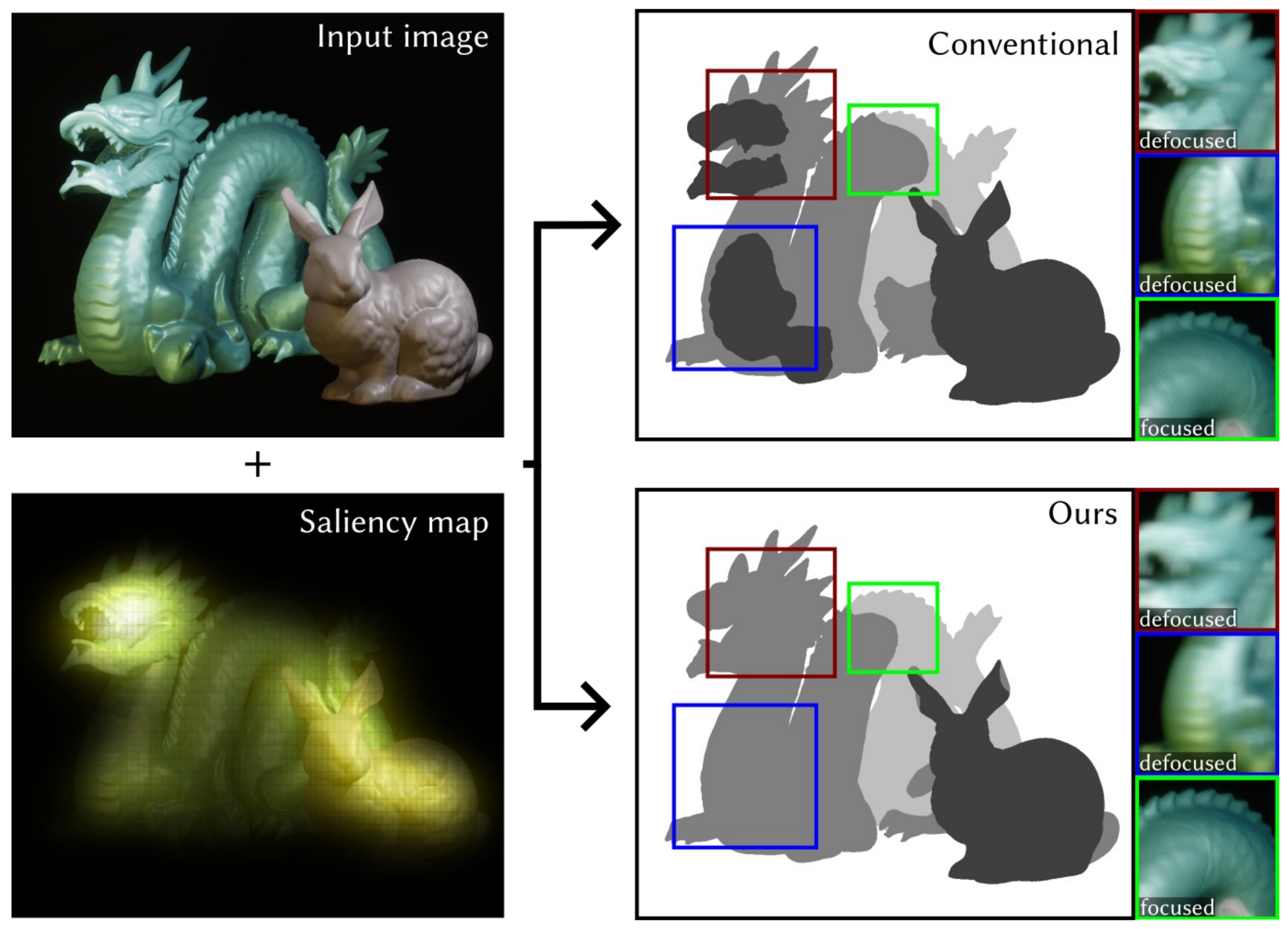

Fig. 4 (left)The input image and the saliency map. (right) The quantized depth maps of the the input image using the conventional method (right-top), and our method (right-bottom)

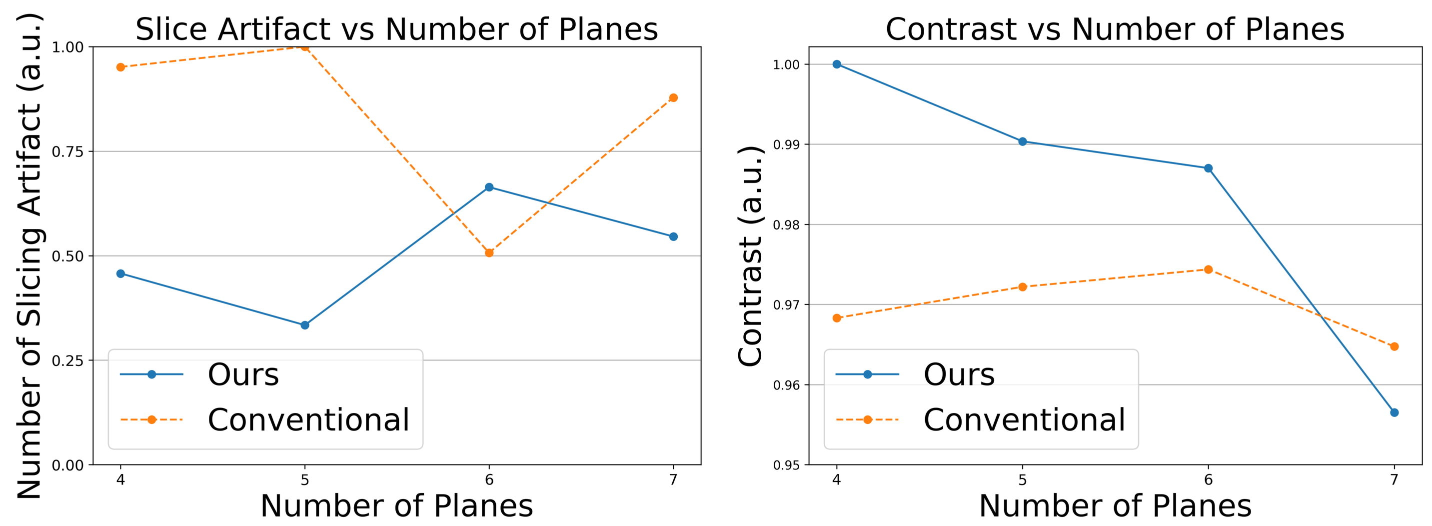

Fig.5 The plots show the contrast and the number of slicing artifacts relative to the number of planes.

CONCLUSIONS

1. Our method reduces the slicing artifact up to 48%.
2. Our method shows up to 2% improvements in contrast for different numbers of focal planes.
3. The comparison results indicate similar performance in image quality metrics, including PSNR, SSIM, LPIPS, and DISTS.
4. In the future, this optimization can be accelerated using a learned approach and integrated into 3D CGH pipelines. Additionally, new targeting scheme on focal surfaces can be investigated by taking advantage of the emerging focal surface beam propagation model[6].

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