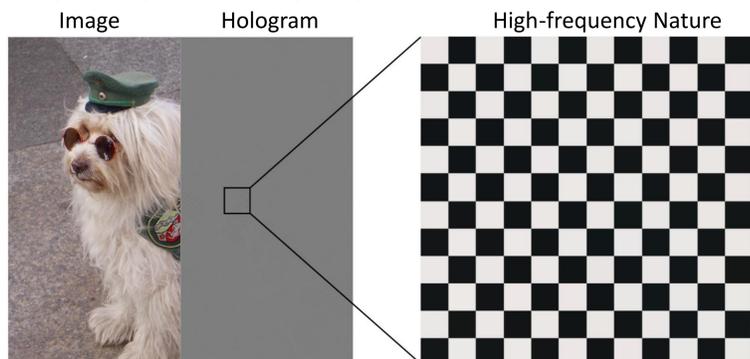




I. PROBLEM

Effective compression of double-phase holograms remains challenging due to their high-frequency nature, impeding the practicality of holographic displays, posing challenges in streaming holograms.



II. RELATED WORK

GaussianImage [5]

- A Gaussian Splatting-based image representation method
- Serve as our baseline
- **Effective for conventional images, but not for holograms (see Figure 1)**

Recent deep learning approaches [4]

- Effective for phase-only hologram
- **Lower compression ratio**
- **Mediocre visual quality**
- **Long training time**

III. OVERVIEW

We introduce a decomposition-based compression framework built on our modified GaussianImage algorithm, tailored for double-phase holograms. We leverage their intrinsic checkerboard pattern structure by partitioning them into complementary components, intending to bypass the high-frequency nature from the outset. Each component is optimized using a reduced set of 2D Gaussian primitives, resulting in a compressed representation. However, hard clamping during rendering in the baseline distorts the underlying distribution, causing blob artifacts. Our framework replaces it with a sinusoidal constraint, which smoothly controls the value range, yielding artifact-free high perceptual quality.

V. RESULTS

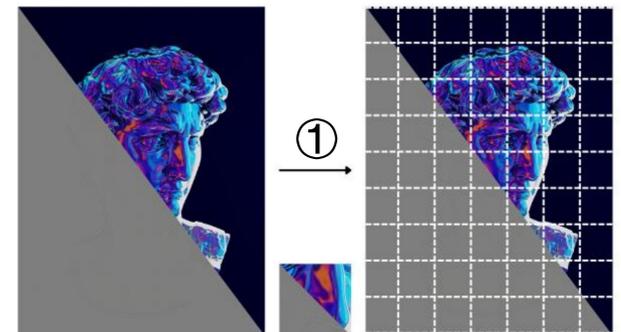
We evaluate the PSNR and SSIM for compressed holograms, experimenting with patch sizes from 64×64 to 512×512 to find the optimal balance between the compression ratio and fidelity. We employ the free-space light propagator from odak [1] to numerically reconstruct holograms over three focal planes spanning a 5 mm depth range and evaluate 3D reconstruction by averaging PSNR, SSIM, and LPIPS across focal planes. As shown in Figure 1, our approach achieves 40.10 dB PSNR with a 26% compression ratio, whereas our baseline, GaussianImage, suffers from severe distortions and low perceptual quality. Unlike conventional learned methods [4] treating holograms as regular images, operating on 64×64 patches (~10s each) and requiring ~26 minutes for 512×512 holograms, our approach enables efficient sequential compression of two components in only ~4 minutes, regardless of resolution, without compromising reconstruction fidelity. Both vertical and horizontal decompositions perform comparably, as shown in Table 1. In our best case, our decomposition utilizes 3% primitive counts compared to the baseline, achieving a compression ratio of 26% while preserving Mean PSNR = 43.39 dB, 0.97 SSIM, and 0.016 LPIPS in the reconstructed scenes. **Compared with the baseline [4, 5], our modification effectively eliminates blob artifacts and inter-patch boundary lines, while introducing moderate computational overhead, doubling the runtime.**

IV. METHODOLOGY

We compress double-phase encoded holograms by utilizing our GaussianImage-based patch-based decomposition framework.

Our Pipeline

- ① Crop the sample hologram into patches
- ② Decompose checkerboard pixels into two components by interleaving columns (vertical) or rows (horizontal)
- ③ Train compressed representation by modified GaussianImage patch-by-patch
- ④ Recombine compressed images by reversing the decomposition process
- ⑤ Combine patches and conduct numerical reconstruction



$$P_{h1} = P[0:2, 0:2], \\ P_{l1} = P[0:2, 1:2],$$

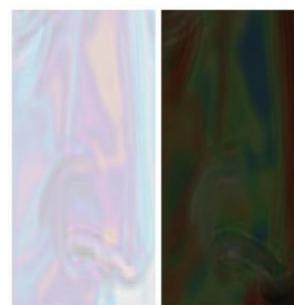
$$P_{h2} = P[1:2, 1:2], \\ P_{l2} = P[1:2, 0:2].$$

Horizontal Decomposition

$$P_{high}^{(h)}[2i, :] = P_{h1}[i, :], P_{high}^{(h)}[2i+1, :] = P_{h2}[i, :]; \\ P_{low}^{(h)}[2i, :] = P_{l1}[i, :], P_{low}^{(h)}[2i+1, :] = P_{l2}[i, :];$$

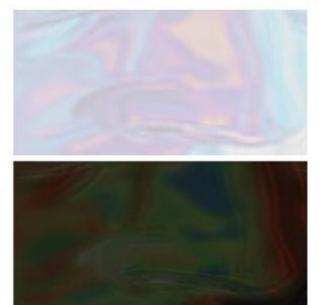
Vertical Decomposition

$$P_{high}^{(v)}[:, 2j] = P_{h1}[:, j], P_{high}^{(v)}[:, 2j+1] = P_{h2}[:, j]; \\ P_{low}^{(v)}[:, 2j] = P_{l1}[:, j], P_{low}^{(v)}[:, 2j+1] = P_{l2}[:, j].$$



GaussianImage

$$\text{output} = \text{clamp}(\text{output}, 0, 1)$$



Our Modification

$$\text{output} = \frac{\sin(\text{output})}{2} + 0.5$$

Figure 1: Comparison between our method and the baseline without decomposition. Each set presents the compressed double-phase holograms with PSNR and SSIM metrics (lower triangle) and the corresponding 3D reconstruction evaluated by PSNR, SSIM, and LPIPS (upper triangle).

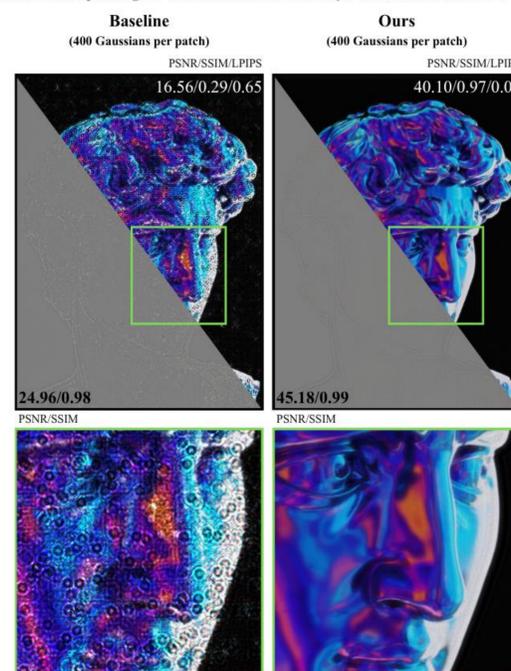


Table 1: Comparison between the baseline with our work (both using RS factorization), with horizontal or vertical decomposition, in hologram fidelity (left) and reconstructed image quality (right) using PSNR and SSIM under equivalent compression ratios (CR).

	Patch Size	Gauss.	PSNR (dB) ↑	SSIM ↑	CR ↓
Baseline	64×64	400	23.40/14.93	0.98/0.16	26%
	128×128	1,600	24.97/15.49	0.98/0.16	26%
	256×256	8,000	26.89/17.50	0.99/0.22	33%
	512×512	32,000	27.92/18.45	0.99/0.25	33%
Ours-Hor.	64×64	400	49.18/43.39	0.99/0.97	26%
	128×128	1,600	48.98/42.80	0.99/0.96	26%
	256×256	8,000	48.88/42.39	0.99/0.96	33%
	512×512	32,000	48.41/41.58	0.99/0.95	33%
Ours-Ver.	64×64	400	49.08/42.84	0.99/0.97	26%
	128×128	1,600	48.93/42.22	0.99/0.96	26%
	256×256	8,000	48.82/41.72	0.99/0.96	33%
	512×512	32,000	48.48/41.22	0.99/0.95	33%

Artifact
FREE

Source Image: exfordy

Source Image: SIMON LEE

AFFILIATIONS



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