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Overcoming deterministic perturbations in physics-informed holographic reconstruction through joint optimization

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Abstract: We propose a novel holographic imaging method that jointly optimizes complex-valued magnitude and mismatched physical parameters to address degraded and erroneous reconstructions caused by physical perturbations.

1. Motivation

In holographic imaging, retrieving the complex-valued wavefield from intensity-only measurements presents an ill-posed inverse problem that has been the focus of extensive research efforts [1–3]. To address data scarcity, untrained methods have gained popularity, combining deep neural networks' implicit priors with physical modeling [2, 3]. While these methods offer promising performance and enhanced interpretability, they heavily depend on the accuracy of the mathematical forward operator model, which may be compromised by physical perturbations like imperfections or misalignments in the optical setup, leading to degraded image quality and erroneous reconstructions. In this paper, we propose a novel approach to address the challenges in physics-informed methods posed by deterministic perturbations, especially in the propagation distance within digital holography configurations. Our method does not require any training data and simultaneously retrieves the complex amplitude map and the range of the object. We demonstrate the feasibility and effectiveness of our model through experimental results and performance evaluation.

2. Network structure

In holographic imaging, we describe the forward operator $\mathscr{H}_z(\cdot)$ mapping the complex-valued wavefield object $O(a,b)$ and measured hologram $I(a,b)$ using the angular spectrum method [1] as

$$I(a,b) = \mathscr{H}_z(O(a,b)) = \|\mathscr{F}^{-1}\{\mathscr{F}\{O(a,b)H(z)\}\}\|^2, \tag{1}$$

where $\mathscr{F}\{\cdot\}$ and $\mathscr{F}^{-1}\{\cdot\}$ are the Fourier transform and inverse Fourier transform respectively. With different propagation distance z, $H(z) = e^{j\frac{2\pi}{\lambda z}\sqrt{\frac{1}{\lambda^2}-f_a^2-f_b^2}}$ stands for the transfer function at each spatial frequency (f_a, f_b). Our method jointly retrieves the complex amplitude map and object range without precise distance knowledge. As shown in Fig 1, we employ two models: $M_{\boldsymbol{w}}(\cdot)$, a UNet structure [4] for intensity and phase predictions, and $M_{\boldsymbol{v}}(\cdot)$, a Transformer-based [5] distance prediction model. The models optimize parameters $\boldsymbol{w}$ and $\boldsymbol{v}$ to generate a synthetic hologram $\hat{I}(a,b) = \mathscr{H}_{\hat{z}}(\hat{O}(a,b))$ through the forward operator that matches the measured hologram. Back-propagation of the consistency loss enables simultaneous recovery of complex amplitude and distance.

3. Results and discussion

We conducted experiments to validate our proposed method for recovering complex-valued amplitude maps under propagation distance perturbations. We compared our approach to the pioneering work of Wang et al. [2], which relies on a physical model of the imaging system. We used a standard USAF pattern to generate a complex-valued object wavefield with correlated amplitude and phase maps. As shown in Fig 2(a), PhysenNet [2], which requires the precise known parameter of $z = 1.065\,\text{mm}$, is severely affected by the mismatched condition ($z = 1.135\,\text{mm}$). The structural similarity index (SSIM) values dropped from 0.87 to 0.25 for amplitude and 0.82 to 0.19 for phase predictions. In contrast, our method gradually recovered the propagation distance, as shown in Fig 2(b), maintaining superior performance with SSIM values above 0.84 for both cases. These results demonstrate that our framework, by jointly optimizing complex-valued amplitude and propagation distance, mitigates model mismatching issues and achieves consistent holographic reconstruction under physical perturbations.

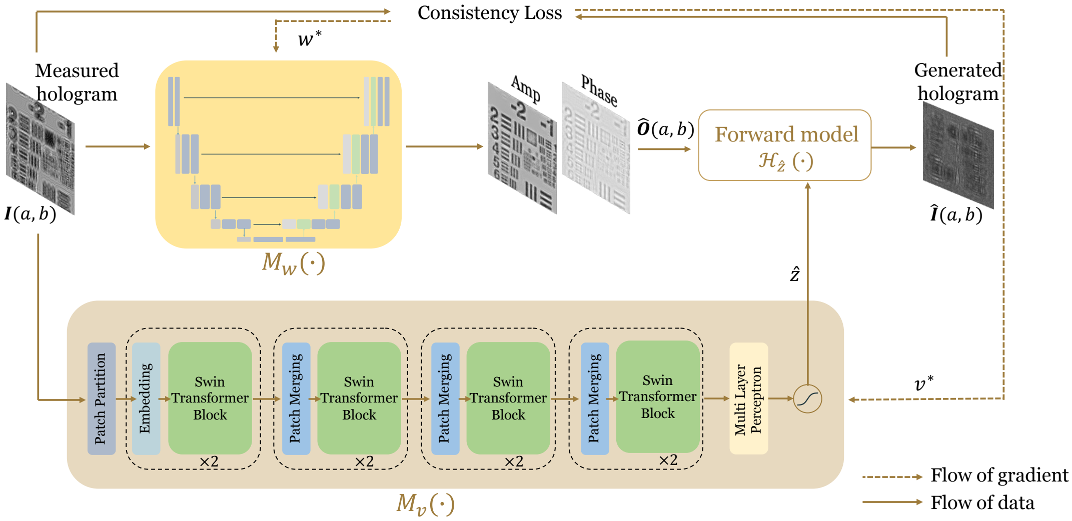

Fig. 1. Proposed framework overview. The framework consists of two models, $M_{\boldsymbol{w}}(\cdot)$ and $M_{\boldsymbol{v}}(\cdot)$, with trainable parameters $\boldsymbol{w}$ and $\boldsymbol{v}$. $M_{\boldsymbol{w}}(\cdot)$ adopts a UNet [4] structure to predict the complex-valued magnitude $\hat{O}(a,b)$, including amplitude and phase maps. $M_{\boldsymbol{v}}(\cdot)$ utilizes the Swin Transformer block [5] to predict the distance $\hat{z}$ from the measured hologram.

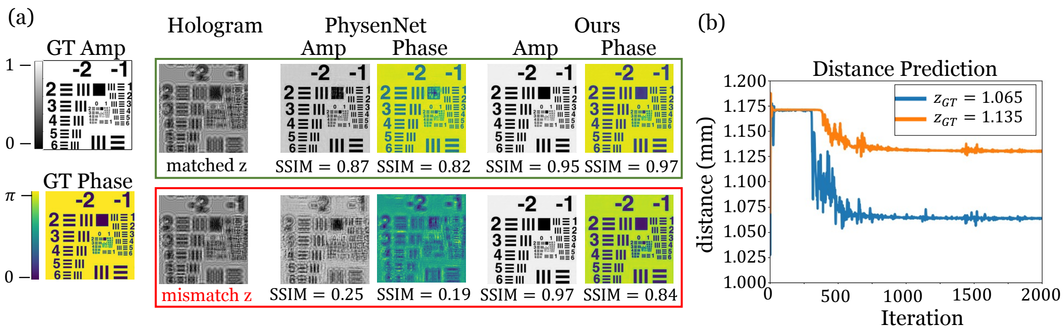

Fig. 2. Impact of distance perturbation on physics-informed reconstruction methods.(a) Comparison of reconstruction performance between PhysenNet [2] and our method under matched and mismatched propagation distances z between the generated hologram and the physical model.(b) Distance prediction results of our proposed method for two different cases.

4. Acknowledgement

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