Single-shot digital holography with improved twin-image noise suppression using a diffusion-based generative model

Yunping Zhang[1], Xihui Liu[1,2], and Edmund Y. Lam[1]

[1]Department of Electrical and Electronic Engineering, The University of Hong Kong, Pokfulam, Hong Kong SAR, China

[2]Institute of Data Science, The University of Hong Kong, Pokfulam, Hong Kong SAR, China

ABSTRACT

Due to the loss of phase information in images captured by intensity-only measurements, the numerical reconstruction of inline digital holographic imaging suffers from the undesirable twin-image artifact. This artifact presents as an out-of-focus conjugate at the virtual image plane and reduces the reconstruction quality. In this work, we propose a diffusion-based generative model that eliminates such defocus noise in single-shot inline digital holography. The diffusion-based generative model learns the implicit prior of the underlying data distribution by progressively injecting random noise in data and then generating high-quality samples by reversing this process. Although the diffusion model has been successful in various challenging tasks in computer vision, its potential in scientific imaging has not been fully explored yet, and one challenge is the inherent randomness in its reverse sampling process. To address this issue, we incorporate the underlying physics of image formation as a prior, which constrains the possible samples from the data distribution. Specifically, we include an extra gradient correction step in each reverse sampling process to introduce data consistency and generate better results. We demonstrate the feasibility of our approach using simulated and experimental holograms and compare our results with previous methods. Our model recovers detailed object information and significantly suppresses the twin-image noise. The proposed method is explainable, generalizable, and transferable to other samples from various distributions, making it a promising tool for digital holographic reconstruction.

1. INTRODUCTION

Conventional optical imaging techniques rely on the one-to-one mapping between the object domain and measurement domains, which can be commonly constructed by an optical system that involves bulky lenses and intricate alignment processes especially for micro-scale or nano-scale objects. As a stark contrast, digital inline holography (DIH) has emerged with immense significance in modern scientific imaging systems with applications ranging from biology and medicine to materials science and engineering.[1–5] By eliminating the need for physical lenses, DIH simplifies the imaging setup, alleviates the painstaking alignment efforts and circumvents optical aberrations that are inevitable in conventional lens-based imaging systems. These advantages make DIH particularly promising for portable and field research applications, which opens up new possibilities for scientific exploration in previously inaccessible environments and real-time monitoring such as micro-plastic investigation in marine system.[6–10]

DIH belongs to the class of coherent imaging system where, instead of a focused image, the complex object information is encoded in the recorded diffraction patterns that are generated from the interference between the scattered light from itself and the unscattered background light.[11] The appropriate computational reconstruction are thus necessitated to digitally recover the scene of the object from the captured measurement. Due to the lack of phase information in the intensity-only measurement, the reconstruction quality of inline holographic imaging is harmed with the twin-image artifacts, which detriments its applications in some biomedical research, particularly with respect to the visualization of cellular or subcellular details of biological structure and activities.[12] To maintain the competitiveness of inline digital holography without compromising its setup simplicity, advanced numerical reconstruction algorithms for single-shot reconstruction have been investigated from a perspective of formulating it as an inverse problem in optical imaging.[13–17] Previous attempts involve an iterative procedure

Send correspondence to Edmund Y. Lam: elam@eee.hku.hk

Computational Optical Imaging and Artificial Intelligence in Biomedical Sciences, edited by Liang Gao, Guoan Zheng, Seung Ah Lee, Proc. of SPIE Vol. 12857, 128570E

· 1605-7422 · doi: 10.1117/12.3000660

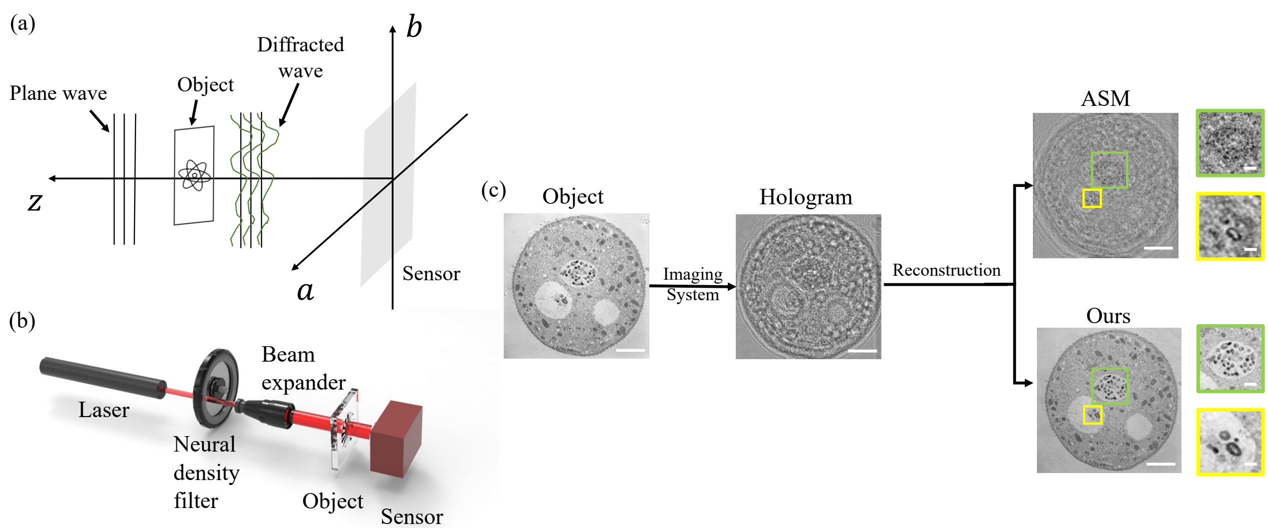

Figure 1. System demonstration of the digital inline holography. (a)Principle demonstration showcasing the imaging process. (b)Physical setup of the optical system. (c)Reconstruction results for a synthetic hologram captured from a convallaria cell. A comparison between the traditional angular spectrum method (ASM) and our proposed method highlights the effectiveness of twin-image noise suppression. Two enlarged region-of-interests (ROIs) are shown on the side for closer examination. The scale bars for the entire field of view (FOV) and two enlarged ROIs: 50 µm, 10 µm and 5 µm.

between the measured plane and the estimated plane, incorporating the *priori* constraints.[13,14,18] However, such approaches require handcrafted image priors and careful parameter tuning to achieve the desired reconstruction performance. On the contrary, deep learning (DL) methods have been shown to provide promising results with superior efficiency in an end-to-end manner.[15–17] The general approach is to train a deep neural network using paired data consisting of holograms and corresponding twin-image-free phase and amplitude information, then using the trained network to reconstruct the twin-image-free results. However, its heavy reliance on large datasets during the training phase is hard or even impractical accessible especially in biomedical imaging applications, considering the dynamic nature and diversity of biological samples. Meanwhile, the purely data-driven nature of DL-based methods often lacks explainability, as the training steps are not readily interpretable.[4,15]

In this article, we develop a novel twin-image noise suppression algorithm for single-shot digital holographic imaging using a diffusion-based generative model. Diffusion models belong to a family of generative models known for capturing complex data distributions and generating high-fidelity samples from unstructured noise vectors. The neural image prior contained in a well-trained diffusion model can be plugged in to various content creation tasks without retraining, which have shown impressive performance in unconditional generative modeling of images.[19,20] We extend its application to the field of holographic imaging in this study. Moreover, to address the inherent randomness of diffusion models, we introduce the physics information of the digital holographic imaging system as a supervisory signal in the generation process. In this way, we eliminate the need for handcrafted design of the image prior and maintain a high level of interpretability specific to the holographic imaging system. Significantly, our approach achieves impressive results without the need for a holographic training dataset. Despite this, it excels in effectively suppressing twin-image noise and accurately reconstructing object information from digital inline holograms.

2. METHOD

2.1 Digital inline holography

To incorporate the physical model of the imaging system, we investigate the imaging process of DIH, as demonstrated in Figure 1. In general, a thin specimen is positioned in front of the sensor at a distance z and illuminated by a reference coherent planar wave $R(a, b)$ with wavelength λ. The recorded hologram $H(a, b)$ is formed by the

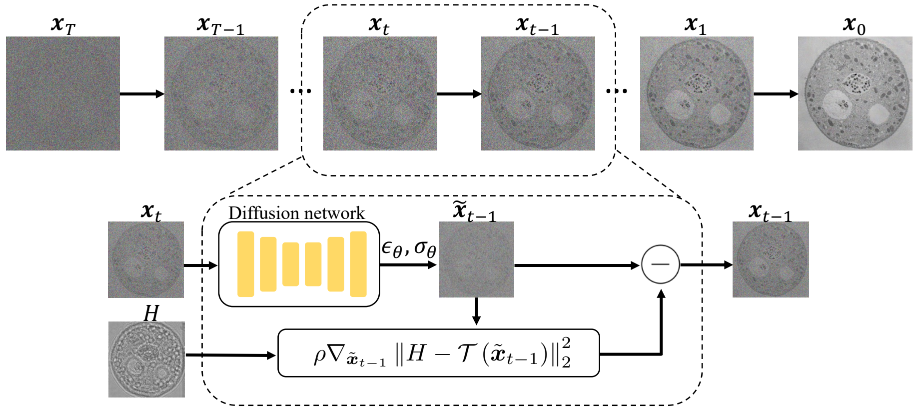

Figure 2. Visual representation of the different components and steps involved in our approach for DIH reconstruction. Each iteration involves the generative process of the diffusion model, guided by the gradient correction of the data consistency.

interference between the diffracted wave $O(a, b)$ from the object and the unscattered reference wave, which is formulated as

$$H(a,b) = |O(a,b) + R(a,b)|^2 = |O(a,b)|^2 + |R(a,b)|^2 + O(a,b)R^*(a,b) + O^*(a,b)R(a,b), \tag{1}$$

where $*$ indicates the complex conjugation. The captured hologram, as described by Eq. 1, encompasses the object wave that is scattered by the object field $x(a, b)$:

$$O(a,b) = \int\int_{\varsigma,\vartheta\in\sum} x(\varsigma,\vartheta)k_z(a-\varsigma, b-\vartheta)d_\varsigma d_\vartheta, \tag{2}$$

where $\sum$ represents the sensor window and k_z denotes represents the 2D propagation kernel at distance z. It is defined using the Fresnel approximation[11] as $h_z(a,b) = \frac{1}{j\lambda z}e^{j\frac{2\pi}{\lambda}}e^{j\frac{\pi}{\lambda z}(a^2+b^2)}$. Therefore, the object information can be recovered if we could find the inverse of the transformation $\mathcal{T}$: $x(a,b) \to H(a,b)$ described by Eq. 1 and Eq. 2. However, the interchangeability of the last two conjugate terms in the solution of Eq. 1 introduces ambiguity and makes this reconstruction under-determined. When the traditional angular spectrum method (ASM) is employed to retrieve the object information, it leads to the formation of twin-image artifacts. These artifacts manifest as out-of-focus conjugates at the virtual image plane, significantly degrading the quality of the reconstruction, as demonstrated in Figure 1(c). Therefore, there is a need for an efficient algorithm to recover the object information accurately from a holographic inline imaging system, addressing the challenges posed by twin-image artifacts and ensuring high-quality reconstructions.

2.2 Generative model with gradient correction

In the context mentioned earlier, the reconstruction of holographic inline imaging can be framed as an inverse problem, where the objective is to find the optimal object information that best reproduces the acquired hologram. To address this problem in an unsupervised learning setup, we propose a novel generative approach that leverages a well-trained diffusion model as a powerful prior, while incorporating the physics information of the imaging system as a guiding constraint. Diffusion models are composed of the forward/diffusion process and reverse process, where the diffusion process progressively disturb the sample until it follows the standard Gaussian noise, and the reverse process aims to recover the clean image by denosing with noise prediction.[21] For an exhaustive review, we recommend referring to the research paper.[21] With the well-trained diffusion model, starting from a normal distribution $x_T \sim \mathcal{N}(0, \mathbf{I})$, high-fidelity and diverse samples x_0 can be generated following the iterative update[†]:

$$\tilde{x}_{t-1} = \frac{1}{\sqrt{\alpha_t}}\left(x_t - \frac{1-\alpha_t}{\sqrt{1-\bar{\alpha}_t}}\epsilon_\theta(x_t,t)\right) + \sigma_\theta^2(x_t,t)\,\delta, \tag{3}$$

[†]For the sake of clarity and simplicity, the lateral coordinates (a, b) is intentionally omitted.

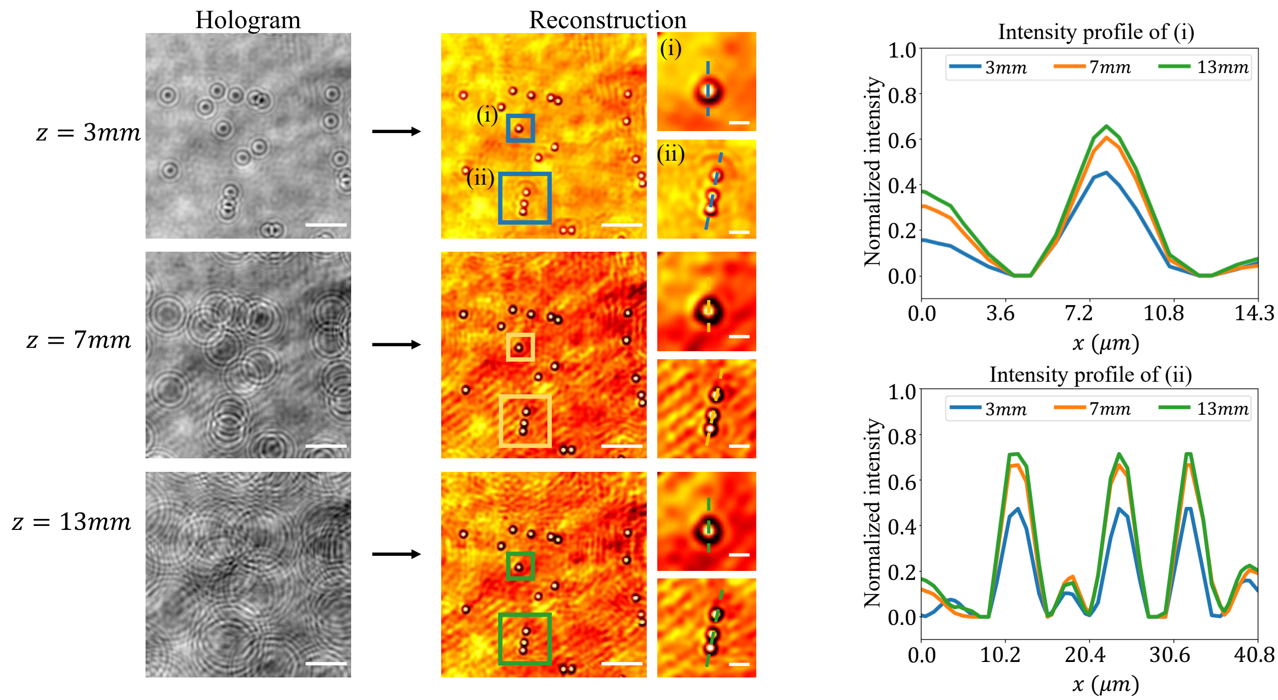

Figure 3. Reconstruction results of an experimental hologram of polystyrene microspheres at various sample-to-sensor distances. The right panel shows the recovered intensity profiles along the dashed line in two enlarged ROIs. Scale bars for the entire FOV, the enlarged ROI (i) and ROI (ii): 50 µm, 5 µm and 10 µm.

where $\delta \sim \mathcal{N}(0, I)$ is the standard Gaussian noise, $\epsilon_\theta(x_t, t)$ and $\sigma_\theta(x_t, t)$ are the output from the well-trained diffusion model[22] given the input x_t at step t. To mitigate the randomness and achieve the desired inference result that aligns with the recorded hologram, we introduce guidance from the hologram H at each iteration. This is accomplished by incorporating the gradient of data consistency. Specifically, the correction step is added after each iteration sampling process:

$$x_{t-1} = \tilde{x}_{t-1} - \rho \nabla_{\tilde{x}_{t-1}} \left\| H - \mathcal{T}(\tilde{x}_{t-1}) \right\|_2^2, \tag{4}$$

where ρ is the step size and $\mathcal{T}(\cdot)$ is the forward transformation of the DIH system defined in Section 2.1. The overall process of the proposed method is demonstrated in Figure 2.

3. EXPERIMENT AND RESULTS

We validate the feasibility of our proposed method by conducting experiments on both synthetic and real holograms. In our simulations, we utilize open-source biological cell images.[23] Figure 1(c) visually illustrates the prevalent twin-image contamination in the reconstruction result obtained using the traditional ASM method. Conversely, our proposed method effectively mitigates this disturbance, as evident from the comparison of two enlarged regions of interest (ROIs) where fine details of the cell structure are resolved.

To rigorously evaluate the performance of twin-image suppression, we employed quantitative evaluation metrics, including the peak signal-to-noise ratio (PSNR), the Structural Similarity Index Measure (SSIM), and the root mean square error (RMSE), utilizing the ground truth object map. The evaluation results demonstrate a substantial improvement in the PSNR value, increasing from 12 dB to 19.88 dB. Furthermore, our method yields a significantly lower MSE value of 0.01, demonstrating its effectiveness in mitigating the twin-image disturbance. Moreover, our method exhibits a higher SSIM value of 0.81, surpassing the SSIM value of 0.23 obtained by the traditional ASM technique. This elevation underscores our method's superior preservation and recovery of structural details.

In our experiments with real holograms, we utilized a publicly available experimental dataset of 3 µm polystyrene microspheres.[24] The diffraction patterns are generated using a laser beam with a wavelength of 532 nm and recorded using an sCMOS camera with a pixel pitch of 6.5 µm. The recorded holograms are obtained at different depths ($z = 3$ mm, $z = 7$ mm, and $z = 13$ mm), resulting in overlapping diffraction fringes of the particles depending on the distance. As depicted in Figure 3, our proposed method consistently delivers accurate reconstruction results across all object-to-sensor distances. To facilitate visual inspection, intensity profiles are plotted along selected interest lines at different distances, revealing a remarkable agreement among the results. The profile figures further demonstrate the successful recovery of the spherical particle appearance, characterized by well-defined and sharp borders.

4. CONCLUSION

In this study, we propose a novel diffusion-based generative model to address the twin-image artifact in digital inline holography. By incorporating the physics of image formation as a prior constraint, our method effectively suppresses twin-image noise and improves reconstruction quality. Experimental results on synthetic and real holograms demonstrate the efficacy of our approach in recovering detailed object information and significantly reducing twin-image disturbance. The proposed method shows promise for digital holographic reconstruction and has potential applications in scientific imaging such as the non-invasive and high-throughput imaging of living cells and other microbiological objects.

5. ACKNOWLEDGEMENTS

This work is supported by the Research Grants Council of Hong Kong (GRF 17201620, GRF 17201822, RIF 7003-21).

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