Applications of Deep Learning in Computational Imaging with Structured Illumination

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ABSTRACT

Structured illumination(SI) has a wide range of applications in computational imaging in the form of encoding and recomposing image signals. In this work, we explore the applications and advantages of deep-learning techniques in SI imaging problems. (1) In single-pixel imaging(SPI), where SI encodes the target into a sequence of bucket signals, the recovery suffers from loss of imaging quality due to various noises. We propose an unsupervised deep-learning (UnDL) based anti-noise approach, which outperforms conventional single-pixel imaging methods considerably in reconstructing targets against noise. (2) In blind ghost imaging, we propose two hybrid quantum-classical machine learning algorithms and a physical-inspired patch strategy, leveraging quantum machine learning to restore high-quality images where classical machine learning fails. (3) In structured illumination microscopy(SIM), the illumination encodes high-frequency details into the passband of the objective. Existing optimization-based decoding algorithms are sensitive to noise, while learning-based methods have faithfulness issues. We propose a physics-informed deep learning approach, where the re-parameterized network outperforms its counterparts in terms of noise robustness and recovery faithfulness. In general, the proposed deep-learning-based algorithms solve the inverse SI decoding problem by leveraging inherent priors of neural networks. The proposed framework and idea have the potential to be applied in other scenarios with SI and other computational imaging problems.

Keywords: structured illumination, deep learning, ghost imaging, structured illumination microscopy

1. INTRODUCTION

Structured illumination(SI) is widely applied in computational imaging scenarios, including single-pixel imaging(SPI),[1] fourier ptychography(FP),[2] structured illumination microscopy(SIM).[3] SI generally acts as a set of known modulation functions, which encodes the target into a sequence of measurements under some specific physical model. To recover the target profile, the measurements go through an explicit decoding algorithm. The decoding algorithms need to be carefully designed since the inverse problem is often ill-posed or under-determined.

Deep learning and neural networks[4,5] are a powerful tool to solve such inverse problems. Benefited by the hardware revolution and large-scale dataset collection, deep learning has witnessed rapid development in the past few years and has been applied in various computational imaging problems(e.g. phase retrieval,[6] scatter imaging,[7] computational ghost imaging,[1] super resolution,[8] low photon imaging[9] and pattern analysis[10]). The success of deep learning is largely attributed to the ability to learn from large-scale datasets by supervised training, or the inherent priors of neural networks.[11]

In this work, we explore the applications and advantages of deep learning techniques in computational imaging problems *with SI*. (1) **Single-Pixel Imaging(SPI).** SI encodes the target into a sequence of 1-D bucket signals, from which the 2D object needs to be recovered. (2) **Blind Ghost Imaging.** Different from classic SPI, the object image is recovered without any knowledge of the modulated speckles. (3) **Structured Illumination Microscopy(SIM).** SI encodes high-frequency details into the passband of the objective. The high resolution image needs to be recovered from original and cosine illumination patterns. Our simulations and experiments demonstrate that firstly, deep neural networks are advantageous in recovering image signals from measurements

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produced by SI. The deep networks are integrated by specific physical models, either in a supervised or unsupervised manner. Secondly, benefited by the strong feature representation ability, quantum networks and the hybrid ones are powerful in more difficult problems like blind ghost imaging. The proposed framework and idea have the potential to be applied in other SI scenarios or more general imaging problems.

2. SINGLE-PIXEL IMAGING

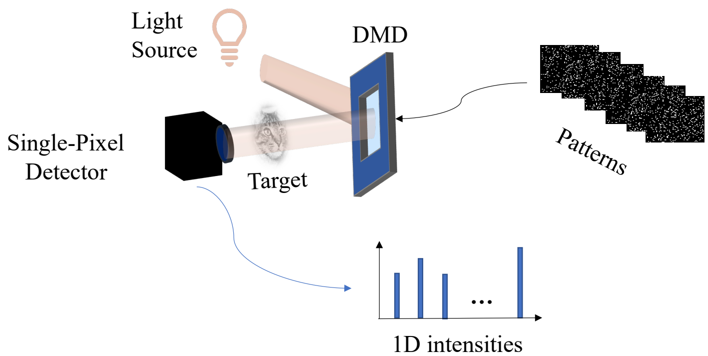

Figure 1. A single-beam single-pixel imaging system.

Physical Model. Fig 1 illustrates a simple single-pixel imaging system. The digital DMD is illuminated by a laser beam and modulates the light field, which propagates towards and interact with the object. Then the transmitted(or reflected) light is collected by a single-pixel detector. A set of patterns $P_t(t = 1, \dots, M)$ are continuously loaded onto the DMD to produce different structured illumination, which then results in a sequence of 1-D measurements $\mathcal{B} = \{B_t\}_{t=1}^{M}$. Formally

$$B_t = \sum_{\mathbf{r}} P_t(\mathbf{r}) \cdot S(\mathbf{r}) d\mathbf{r} \tag{1}$$

Then the inverse problem can be expressed as

$$\hat{S} = \arg\min_{S} \sum_{t=1}^{M} \|P_t \cdot S - B_t\|_2 \tag{2}$$

When sampling number M is small, the optimization is highly under-determined and traditional methods fail.

Method. The proposed UnDL framework is illustrated in Fig. 2, which consists of an imaging module and an enhancing module. The imaging module and enhancing module are trained in a two-stage manner. After training, the inference can be finished in one single forward pass. (1) **Imaging module training.** We add noise with zero-mean to clear images and simulate 1-D measurements $\mathcal{B}$ with the sampling rate randomly chosen from 5% and 10%. $\mathcal{B}$ goes through DGI[12] and obtain a reference image $\tilde{S}$. Then the imaging module is trained with paired data $\{(\mathcal{B}, \tilde{S})\}$ and standard MSE loss. (2) **Enhancing module training.** When the training of imaging module finishes, the enhancing module is trained in a self-supervised way. Specifically, we randomly sample sub-regions from the outputs of imaging module, mask out one pixel in the sub-region, and use its neighboring pixels to predict its value. The idea is similar to MAE.[13] The image quality from the imaging module is largely improved by the enhancing module. **Inference.** After training, UnDL is completely end-to-end, taking real measurements as input and producing reconstructions.

Results. We report the simulation and experimental results in Fig. 3. In subplot (a), we compare the proposed UnDL framework against DGI[12] and CSTV.[14] The PSNR is evaluated across MNIST dataset with the sample rate $5\%, 10\%, 20\%$ respectively. It can be seen that the proposed approach consistently outperform the others. This is also verified in subplot (b), where the digit 5 recovered by ours approach is more clear and less affected by under-sampling and noise. In subplot (c), we experimentally demonstrate the superiority using a butterfly wing. The recovery and its line profile show that UnDL can produce more high-quality reconstructions.

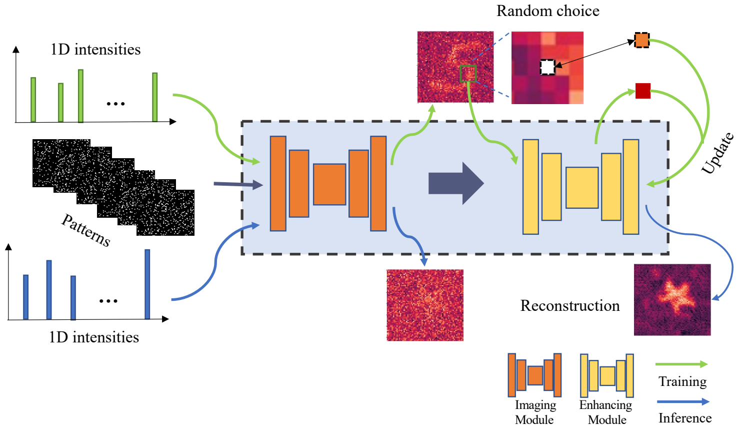

Figure 2. The proposed UnDL framework for single-pixel imaging.

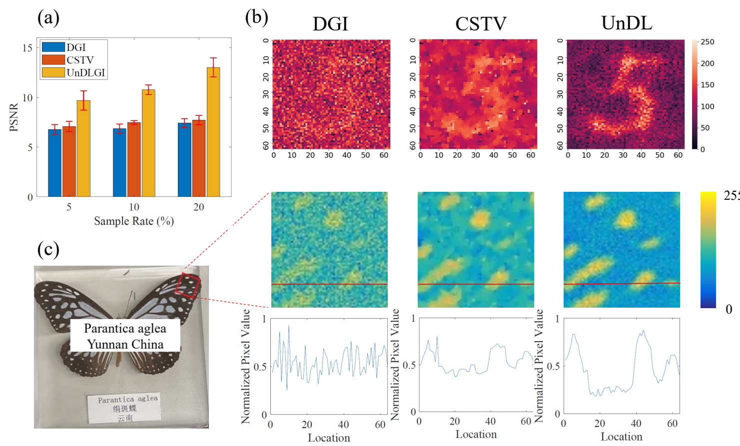

Figure 3. The simulation and experimental results of UnDL for single-pixel imaging.

3. BLIND GHOST IMAGING

Physical Model. The physical process and forward model is the same as Sec. 2 and Fig. 1, except that in blind ghost imaging, we need to recover the image without any priori or knowledge of the illumination patterns.

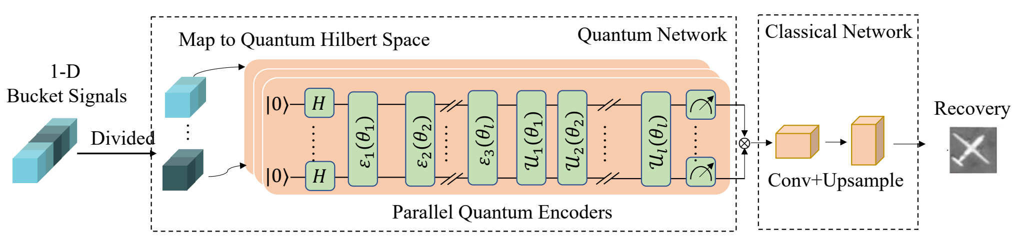

Figure 4. The proposed hybrid quantum-classical network for blind ghost imaging.

Method. We propose a hybrid quantum-classical neural network, which has a more powerful representation ability than pure classic ones. As illustrated in Fig. 4, the bucket signals are first divided into several segments and fed into parallel quantum encoders. A quantum encoder consists of several variational quantum layers, which progressively process quantum features in Hilbert space. After that, each qubit is measured locally to estimate the predefined observable $O = \otimes_{i=1}^{n} Z_i$ as the output. Outputs from parallel branches are then concatenated into a single vector, which is post-processed by a classic convolutional neural network(CNN). The CNN consists of interleaved upsampling layers and convolutional layers to recover original image size.

The proposed quantum-classical neural network $f_\theta(\cdot)$ is trained in a supervised manner. Specifically, given a target image S, 1-D measurements $\mathcal{B}$ are simulated according to Eq. 1. Then the quantum-classical neural network is trained with standard MSE loss

$$\theta^* = \arg\min_{\theta} \sum_{n} \|f_\theta(\mathcal{B}_n) - S_n\|_2 \tag{3}$$

Results. We compare the proposed quantum-classical neural network with a pure classical one and report the results in Fig. 5. With the same sampling, the hybrid quantum-classical network produces more high-quality reconstructions. It can be seen that the pure classical network almost fails at all sampling levels, which originates from the convergence issue under blind ghost imaging. In contrast, the hybrid quantum-classical network recovers the rough shape of the airplane, and the reconstruction quality improves as the sampling level increases. The results have proved the advantages of quantum machine learning in feature processing and encoding.

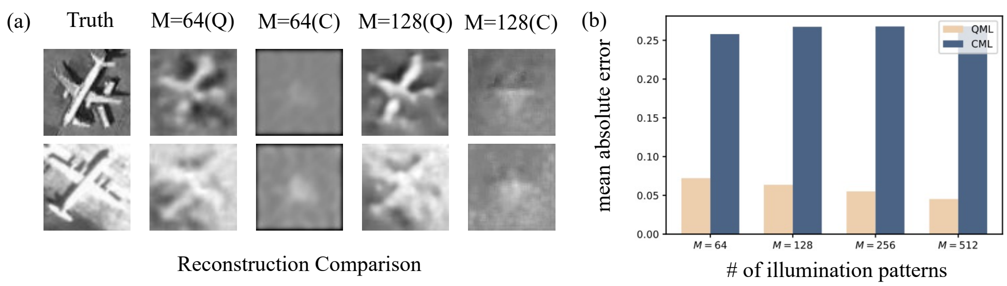

Figure 5. Simulation results of the proposed quantum-classical neural network for blind ghost imaging.

4. STRUCTURED ILLUMINATION MICROSCOPY

Physical Model. In structured illumination microscopy(SIM, Fig. 6(a)), the object is illuminated by cosine patterns $P_{d,\varphi} = 1 + c_d \cdot \cos(2\pi \mathbf{p}_d \cdot \mathbf{r} + \varphi_d)$. Cosine patterns shift the high-frequency details of the object $S(\mathbf{r})$ into the passband of the objective ($h(\mathbf{r})$). By varying the orientation and phase of the patterns, a set of SIM images $\mathcal{I} = \{I_t\}_{t=1}^{M}$ is produced. Formally we have the forward model in Eq. 4 and the inverse model in Eq. 5. Classic numeric-based[3,15] or optimization-based[16] methods could produce artifacts, especially when the illumination vector is not accurately estimated, or when the signal-to-noise is low.

$$I_t(\mathbf{r}) = (S(\mathbf{r}) \cdot P_t(\mathbf{r})) \otimes h(\mathbf{r}) \tag{4}$$

$$\hat{S} = \arg\min_{S} \sum_{t} \|(P_t \cdot S) \otimes h - I_t\|_2 \tag{5}$$

Method. To achieve robust and faithful super-resolution recovery profiles, we propose a physics-informed neural network with a specially designed architecture and optimization objective(Fig. 6(b)(c)). (1) The physics-informed neural network $f_\theta(\cdot)$ consists of a group-wise feature extraction module $f_{\theta_g}(\cdot)$ and a fusion module $f_{\theta_h}(\cdot)$. Inspired by the fact that raw images in SIM come in groups(determined by pattern orientations), the group-wise feature extraction module consists of several group convolutional blocks to progressively extract features. Then the fusion module aggregates the features and reconstructs the super-resolution image. (2) To avoid the recovery being over-smooth, we propose a fourier-space objective function, constraining the predicted frames and captured frames in the fourier space.

$$\mathcal{L}_{fourier} = \sum_{t} \|\mathcal{F}(\hat{I}_t) - \mathcal{F}(I_t)\|_2 \tag{6}$$

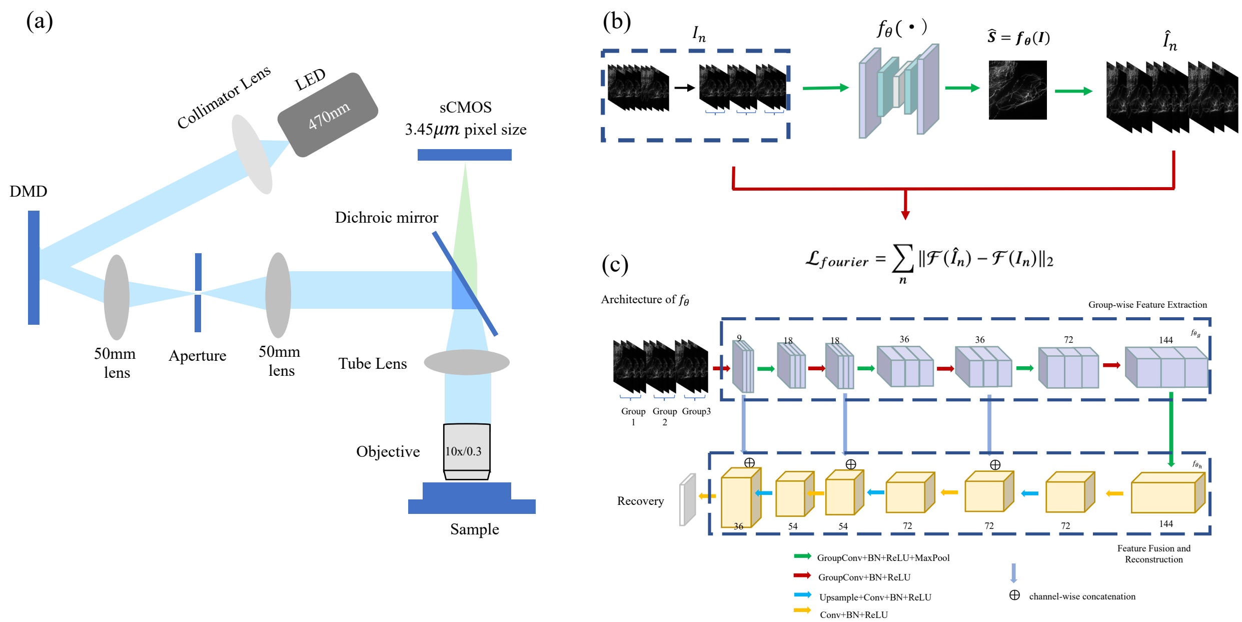

Figure 6. (a) A LED and DMD based SIM system. (b) The proposed physics-informed network and training method for SIM. (c) The detailed architecture of the neural network.

Formally, the network takes raw images as input and outputs the high-resolution estimation $\hat{S} = f_\theta(\mathcal{I})$. The high-resolution estimation goes through the forward model Eq. 4, producing the low-resolution estimations $\hat{I}_t = (P_t \cdot \hat{S}) \otimes h$. Fourier-space consistency between these estimations and raw images is derived according to Eq. 6 to update the network parameters until convergence.

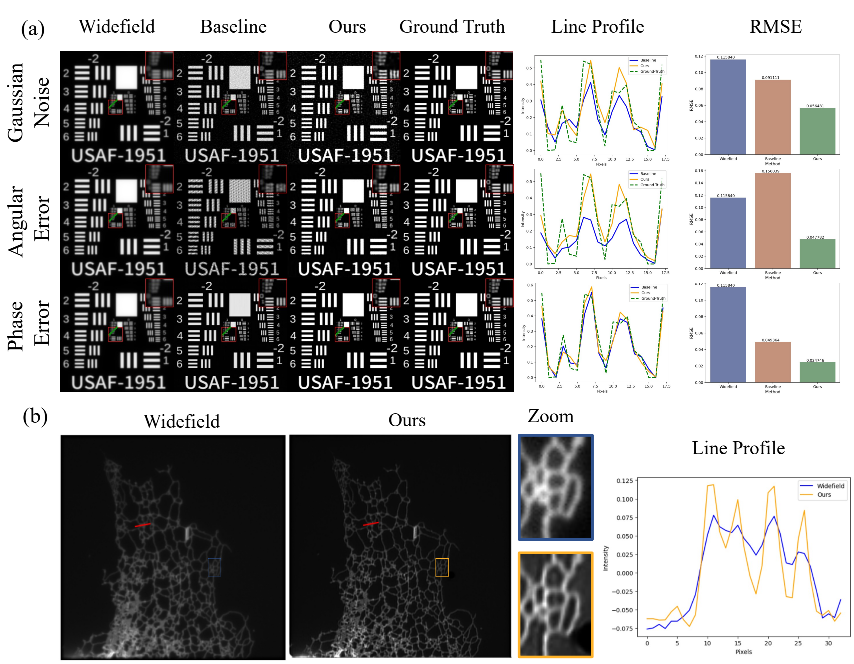

Figure 7. Simulation and experimental results of the proposed physics-informed neural network for SIM.

Results. We first report simulation results under several noisy scenarios in the upper part of Fig. 7. Noisy scenarios include gaussian noise, inaccurate parameter estimation and lens aberration. The proposed physics-informed neural network is more robust and consistently outperforms the baseline.

We also verify the proposed approach on open-source experimental database[17] and report in the lower part of Fig. 7. More fine-grained details can be observed from the comparison against widefield image.

5. CONCLUSION

In this work, we explore the applications and advantages of deep learning in computational imaging problems with structured illumination. We have focused on three representative scenarios: single-pixel imaging, blind ghost imaging and structured illumination microscopy. Simulations and experiments have demonstrated that, by integrating with specific physical models, the deep neural networks are advantageous in recovering image signals encoded by SI. We have also demonstrated the power of quantum networks in some difficult SI problems like blind ghost imaging.

REFERENCES

[1] Lyu, M., Wang, W., Wang, H., Wang, H., Li, G., Chen, N., and Situ, G., "Deep-learning-based ghost imaging," *Scientific reports* **7**(1), 17865 (2017).

[2] Nguyen, T., Xue, Y., Li, Y., Tian, L., and Nehmetallah, G., "Deep learning approach for fourier ptychography microscopy," *Optics express* **26**(20), 26470–26484 (2018).

[3] Gustafsson, M. G., Agard, D. A., and Sedat, J. W., "Doubling the lateral resolution of wide-field fluorescence microscopy using structured illumination," in [*Three-Dimensional and Multidimensional Microscopy: Image Acquisition Processing VII*], **3919**, 141–150, SPIE (2000).

[4] LeCun, Y., Bengio, Y., and Hinton, G., "Deep learning," *nature* **521**(7553), 436–444 (2015).

[5] Dong, S., Wang, P., and Abbas, K., "A survey on deep learning and its applications," *Computer Science Review* **40**, 100379 (2021).

[6] Sinha, A., Lee, J., Li, S., and Barbastathis, G., "Lensless computational imaging through deep learning," *Optica* **4**(9), 1117–1125 (2017).

[7] Li, S., Deng, M., Lee, J., Sinha, A., and Barbastathis, G., "Imaging through glass diffusers using densely connected convolutional networks," *Optica* **5**(7), 803–813 (2018).

[8] Nehme, E., Weiss, L. E., Michaeli, T., and Shechtman, Y., "Deep-storm: super-resolution single-molecule microscopy by deep learning," *Optica* **5**(4), 458–464 (2018).

[9] Goy, A., Arthur, K., Li, S., and Barbastathis, G., "Low photon count phase retrieval using deep learning," *Physical review letters* **121**(24), 243902 (2018).

[10] Feng, S., Chen, Q., Gu, G., Tao, T., Zhang, L., Hu, Y., Yin, W., and Zuo, C., "Fringe pattern analysis using deep learning," *Advanced Photonics* **1**(2), 025001–025001 (2019).

[11] Ulyanov, D., Vedaldi, A., and Lempitsky, V., "Deep image prior," in [*Proceedings of the IEEE conference on computer vision and pattern recognition*], 9446–9454 (2018).

[12] Ferri, F., Magatti, D., Lugiato, L., and Gatti, A., "Differential ghost imaging," *Physical review letters* **104**(25), 253603 (2010).

[13] He, K., Chen, X., Xie, S., Li, Y., Dollár, P., and Girshick, R., "Masked autoencoders are scalable vision learners," in [*Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*], 16000–16009 (2022).

[14] Bian, L., Suo, J., Dai, Q., and Chen, F., "Experimental comparison of single-pixel imaging algorithms," *JOSA A* **35**(1), 78–87 (2018).

[15] Gustafsson, M. G., "Surpassing the lateral resolution limit by a factor of two using structured illumination microscopy," *Journal of microscopy* **198**(2), 82–87 (2000).

[16] Dong, S., Nanda, P., Shiradkar, R., Guo, K., and Zheng, G., "High-resolution fluorescence imaging via pattern-illuminated fourier ptychography," *Optics express* **22**(17), 20856–20870 (2014).

[17] Christensen, C. N., Ward, E. N., Lu, M., Lio, P., and Kaminski, C. F., "Ml-sim: universal reconstruction of structured illumination microscopy images using transfer learning," *Biomed. Opt. Express* **12**, 2720–2733 (May 2021).