Coded wavefront sensor and non-iterative learning-based reconstruction

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Abstract: Here we put forward a coded wavefront sensor and neural network framework to achieve wavefront reconstruction. The new framework outperform the preview method not only in the speed but also in the accuracy.

1. Introduction

In biomedical imaging, optical aberration will happen when the light goes through the intracellular fluid material and some transparent tissue. The wavefront sensor plays an essential role in optical aberration correction and compensation. The wavefront sensor we used in this paper is the coded wavefront sensor [1]. We placed a binary code pattern in front of the camera. We first captured the image without any distortion as a reference. Then when the wavefront change, the distortion also changes. Then we can infer the wavefront from the distortion of the captured image and reference image.

Most of the preview wavefront sensor reconstruction methods are optimization-based iterative method [1], which need a very long time to handle the large image. Because this inverse problem is under-determined, people add some hand-craft prior to solve it. However, firstly, design the hand-craft prior is always very time-consuming. Secondly, it is not easy to find an excellent hand-craft prior to fit all scenes and have a good reconstruction result. Recently, there is some advance in using deep learning in the phase retrieval problem. However, most of them are the iterative method. [2]

However, in this project, we put forward a deep learning non-iterative method. This can have better performance than the preview method not only in the speed but also in the accuracy.

2. Principle

2.1. Coded Wavefront Sensor

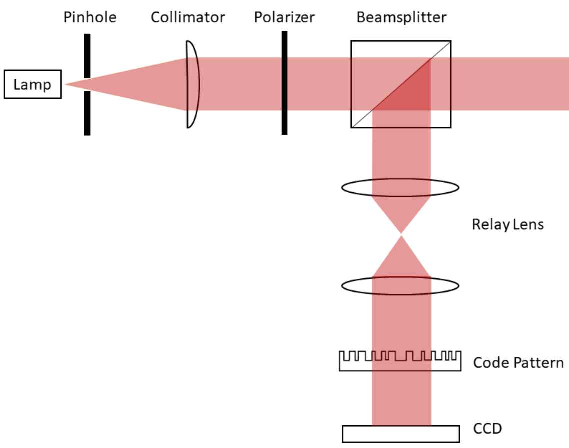

Fig. 1. Coded Wavefront Sensor

The coded wavefront sensor is showing in Figure 1. We place a binary code pattern in front of the camera. The reference image I_0 is captured in a planar wavefront. When the object wavefront change, there is distortion. We capture another image I. We can infer the wavefront from the distortion. The whole process can be written as the following equation:

$$\frac{z}{k}\nabla\phi(\mathbf{r})\cdot\nabla\mathbf{I_0}(\mathbf{r})+\mathbf{I}(\mathbf{r})-\mathbf{I_0}(\mathbf{r})=\mathbf{0} \tag{1}$$

z is the distance between the mask camera. $k = 2\pi/\lambda$ is the wave number. The setup is shown in Figure 1. The wavefront is displayed by the SLM.

2.2. *related work*

The Metzler proposed the prDeep unrolled neural network [2]. The author use the idea of the RED [3] and plug-and-play prior [4]. In the plug-and-play prior paper, the author use the denoiser(like BM3D) as the projection operator for the prior sub-problem.

2.3. *Simulation and Reconstruction*

Because all the physical process is well-understood [5], we built a simulation code base on the Fast Fourier Transform for the wave propagate in the free space [6]. The input of simulation data is human bone captured by ptychography from [7]. The resolution is 256×256 grayscale image. The sensor pixel size is 6.45×10^-6. The binary mask pattern is placed 1.5mm before the CCD. The wave length is 550nm.

We built an attention UNet [8] for reconstruction. The attention UNet is made of encoder and decoder. It has good performance in this kind of image reconstruction task.

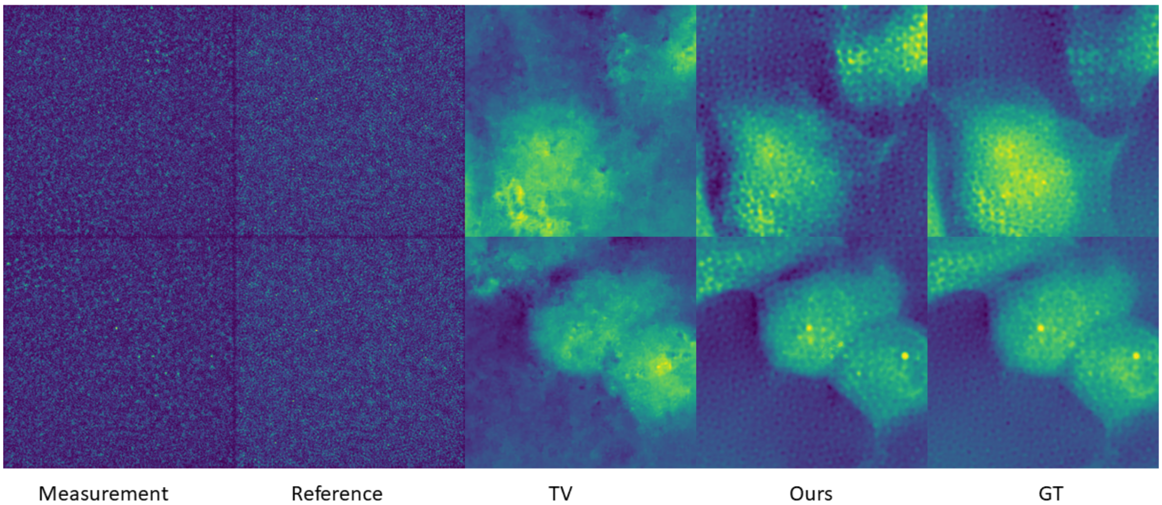

Fig. 2. Reconstruction Result Comparison

There is a lot of small structure in the biological imaging, which will be a challenging problem for the prior-based method. We can see from the Figure 2. The TV prior method result is very smooth. All the detailed structure is lost. Meanwhile, our deep learning method result can reconstruct even the small bubble in the image very well. The metrics result in our method outperform the TV-prior method by 9dB in PSNR and 0.4 in SSIM.

3. Conclusion

In this paper, we put forward a very simple wavefront measurement method based on the image's distortion. We tried a deep learning method for the reconstruction algorithm. The result outperforms the preview prior-based method. This enables such wavefront sensor to become practical in the biological image and nanostructure reconstruction task.

References

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