

Plug-and-Play Deep Image Prior for Snapshot Optical Coherence Tomography

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Abstract: In snapshot optical coherence tomography (OCT), the spectral data is sampled by a coded aperture snapshot spectral imaging (CASSI) system. A self-supervised neural network is developed that integrates deep image priors (DIP) into the plug-and-play regime for the reconstruction of 3D tomographic information. © 2023 The Author(s)

1. Introduction

Optical Coherence Tomography (OCT) [1] is a non-invasive optical imaging technology that utilizes interferometry to acquire high-resolution images of biological tissues. By measuring the back-scattered light from the tissue, OCT can provide cross-sectional and three-dimensional images of biological structures with micrometer-level resolution, which makes it a powerful tool for biomedical research and clinical applications. Compared to traditional medical imaging modalities such as X-ray, CT, and MRI, OCT offers advantages in terms of resolution, imaging speed, and absence of ionizing radiation.

2. Principle

The spectral data cube (x, y, λ) is unusually detected with point scanning or an array detector with high-speed swept laser source in some typical OCT techniques, which are time-consuming and the information is highly redundant. Here we consider snapshot compressive imaging (SCI) method [2,3]. The spectral data of OCT is sampled by a well-built coded aperture snapshot spectral imaging (CASSI) system [4], with which the 3D tomographic information of the object is captured in a snapshot and compressed as a 2D measurement. The experimental setup of snapshot OCT is shown in Fig. 1.

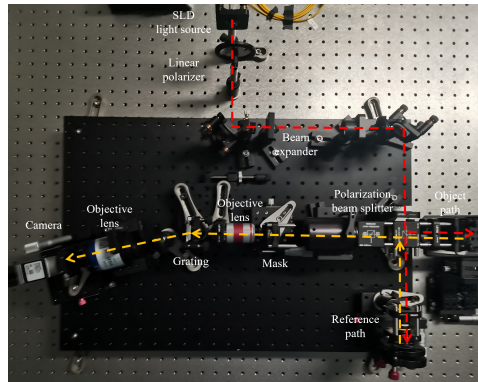


Fig. 1. The experimental setup of snapshot OCT.

As for reconstruction, we need to first reconstruct the spectral data cube (x, y, λ) from the 2D measurement. The previous works have demonstrated satisfying results with deep learning for CASSI reconstruction [5, 6]. But these methods usually need large amount of data for training, which is time-consuming and lacks flexibility. Thus, we develop an untrained neural network that integrates deep image prior (DIP) [7] into the plug-and-play (PnP) regime for snapshot OCT's reconstruction. In this work, we implement alternating direction method of multipliers (ADMM) [8] with both TV and DIP prior for CS-OCT's reconstruction, the iterative process is illustrated in Fig. 2. Concretely, we use ADMM-TV for the first 100 times iterations to get the preliminary result and then DIP iterates 750 epochs for optimization. What follows is the alternate iterations of ADMM-TV and DIP.

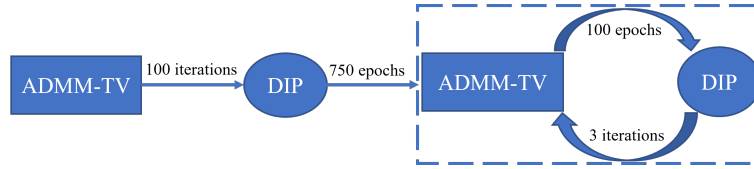


Fig. 2. The schematic of the proposed algorithms.

3. Results and discussion

The experimental data and reconstruction results are shown in Fig.3, in which (a) is the resolution target with characters 'GRID', (b) and (c) are the captured modulation mask and 2D measurement. (d) presents the comparison between conventional iterative algorithms ADMM-TV and proposed ADMM-TV with DIP (only the depths with target information are presented). We can see that the proposed method outperforms the ADMM-TV with smoother edges and less noise in the reconstruction result.

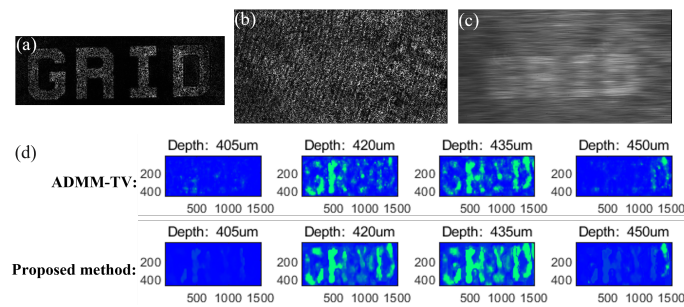


Fig. 3. The experimental data and reconstruction results

4. Conclusion

In this manuscript we present the snapshot OCT system which makes it convenient for OCT's detection and make full use of the redundancy of spectral images. A PnP-DIP method for snapshot OCT's reconstruction is demonstrated, in which the DIP is plugged into the iterative process of ADMM-TV. The experimental results demonstrate the effectiveness and feasibility of the proposed method. We would further improve the reconstruction results of the proposed method in the follow-up works and make a comparison with state-of-the-art deep-learning-based reconstruction methods.

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