Model Learning: Primal Dual Networks for Fast MR imaging

Jing Cheng[1], Haifeng Wang[1], Leslie Ying[3], Dong Liang[1, 2](✉)

[1] Paul C. Lauterbur Research Center for Biomedical Imaging, Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences, Shenzhen, Guangdong, China
[2] Research center for Medical AI, Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences, Shenzhen, Guangdong, China
Dong.Liang@siat.ac.cn
[3] Departments of Biomedical Engineering and Electrical Engineering, University at Buffalo, the State University of New York, Buffalo, NY 14260 USA

Abstract. Magnetic resonance imaging (MRI) is known to be a slow imaging modality and undersampling in k-space has been used to increase the imaging speed. However, image reconstruction from undersampled k-space data is an ill-posed inverse problem. Iterative algorithms based on compressed sensing have been used to address the issue. In this work, we unroll the iterations of the primal-dual hybrid gradient algorithm to a learnable deep network architecture, and gradually relax the constraints to reconstruct MR images from highly undersampled k-space data. The proposed method combines the theoretical convergence guarantee of optimization methods with the powerful learning capability of deep networks. As the constraints are gradually relaxed, the reconstruction model is finally learned from the training data by updating in k-space and image domain alternatively. Experiments on in vivo MR data demonstrate that the proposed method achieves superior MR reconstructions from highly undersampled k-space data over other state-of-the-art image reconstruction methods.

Keywords: MR reconstruction, Primal dual, Deep learning.

1 Introduction

Accelerating magnetic resonance imaging (MRI) has been an ongoing research topic since its invention in the 1970s. Among a variety of acceleration techniques, compressed sensing (CS) has become an important strategy during the past decades [1]. In general, the imaging model of CS-based methods can be written as

$$\min_m \frac{1}{2}\|Am-f\|_2^2+\lambda\|\Psi m\|_1 \tag{1}$$

where the first term is the data consistency and the second term is the sparse prior. Ψ is a sparse transform, such as wavelet transform or total variation, m is the image to be reconstructed, A is the encoding matrix, f denotes the acquired k-space data.