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Fast MRI Reconstruction via Edge Attention

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Abstract. Fast and accurate MRI reconstruction is a key concern in modern clinical practice. Recently, numerous Deep-Learning methods have been proposed for MRI reconstruction, however, they usually fail to reconstruct sharp details from the sub-sampled *k*-space data. To solve this problem, we propose a lightweight and accurate Edge Attention MRI Reconstruction Network (EAMRI) to reconstruct images with edge guidance. Specifically, we design an efficient Edge Prediction Network to directly predict accurate edges from the blurred image. Meanwhile, we propose a novel Edge Attention Module (EAM) to guide the image reconstruction utilizing the extracted edge priors, as inspired by the popular self-attention mechanism. EAM first projects the input image and edges into $\mathbf{Q}_{\mathbf{image}}$, $\mathbf{K}_{\mathbf{edge}}$, and $\mathbf{V}_{\mathbf{image}}$, respectively. Then EAM pairs the $\mathbf{Q}_{\mathbf{image}}$ with $\mathbf{K}_{\mathbf{edge}}$ along the channel dimension, such that 1) it can search globally for the high-frequency image features that are activated by the edge priors; 2) the overall computation burdens are largely reduced compared with the traditional spatial-wise attention. With the help of EAM, the predicted edge priors can effectively guide the model to reconstruct high-quality MR images with accurate edges. Extensive experiments show that our proposed EAMRI outperforms other methods with fewer parameters and can recover more accurate edges.

AMS subject classifications: 54H30, 68U03, 68U10, 68T07
Key words: Image restoration, MRI reconstruction, Edge attention.

1 Introduction

Magnetic Resonance Imaging (MRI) is one of the most important tools in image-guided adaptive radiotherapy, which helps doctors locate pathological regions without harmful

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radiation exposure. However, due to Nyquist sampling requirement [31], the imaging time is frustratingly long to get high-quality images from fully-sampled *k*-space data. Nowadays, Parallel Imaging (PI) has become a standard strategy used by most clinical MRI scanners to accelerate the imaging process. PI places multiple receiver coils around the subject, each of which subsamples *k*-space data from different views. Therefore, the overall imaging time can theoretically be reduced by a factor of the coil number.

During the past decades, numerous reconstruction methods have been designed for parallel MR Imaging. Among them, Compressed Sensing (CS) based methods are a broad class of mature and effective methods that are theoretically supported by [5]. CS-based methods exploit the inherent sparsity of MR data in some properly transformed domains and can recover clear images from sub-sampled *k*-space via iteratively solving a constrained optimization problem [17, 28]. Recently, with its great success in various image processing tasks (e.g., image classification [16, 41] and image restoration [9, 45, 51]), Deep learning (DL) has also greatly promoted the development of parallel MR imaging. For example, Chen *et al.* [7] proposed a PC-RNN model with three convolutional RNN (ConvRNN) modules to iteratively learn the features in multiple scales. Aggarwal *et al.* [1] proposed a general model-based image reconstruction framework with a convolution neural network (CNN) based regularization prior. However, existing methods ignore the necessity of edge reconstruction, resulting in a lack of accurate and clear edges in reconstructed MR images.

Edge preserving has always been a crucial concern in the design of reconstruction models. To improve the quality of reconstructed images and preserve image edges, some works suggested introducing edge priors in the original restoration problem to preserve image edges [4, 34]. However, they will suffer from complicated algorithm design and time-consuming training processes. Recently, some more efficient methods have been proposed to use edge maps as external guidance for image restoration. For example, Yang et al. [48] used off-the-shelf edge detectors to extract image edges from the degraded images. Fang et al. [12] predicted image edges by constructing an edge reconstruction network. Huang *et al.* [18] designed a novel dual discriminator GAN framework for solving fast multi-channel MRI, in which one GAN network is built for edge information enhancement. Inspired by these methods, we also consider introducing image edge prior as external guidance to MRI reconstruction since 1) image edges are prominent and distinguishable features in MRI (see Fig. 1), which can serve as a good guide to the model to recover high-frequency details; 2) the ground truth edges can be easily fetched via ordinary edge extraction operators, like Canny, Sobel, and Prewitt, which means that the edge maps can be learned in a data-driven manner. However, how to effectively utilize image edge priors to guide image reconstruction still remains a challenge. In some methods, edge information was simply concatenated with the input image and passed to the next stages. Though this is a simple way to utilize the edge priors, it may not give full play to the guiding role of the edge priors. Therefore, in this work, we want to explore a more efficient and effective mechanism to fully take advantage of image edge priors.

To address the aforementioned issues, in this work, we propose a lightweight and ac-