FUSIONNET: A PARALLEL INTERACTIVE NEURAL NETWORK FOR COMPRESSED SENSING MRI RECONSTRUCTION

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ABSTRACT

Compressed sensing provides the theoretical foundation for magnetic resonance imaging (MRI) reconstruction with undersampled \( k \)-space data with a sampling rate much less than the one required by the Nyquist-Shannon sampling theorem. However, CS-MRI principally relies on iterative numerical solvers which usually suffer from expensive computation cost and accurate handcrafted priori. In this paper, inspired by the popularity of deep learning, we propose a novel cascaded convolution neural network structure, called FusionNet, to accelerate MRI reconstruction. Different from other existing methods, our proposed FusionNet contains two parallel and interactive branches simultaneously performing on \( k \)-space and spatial-domain data. The experimental results show that the proposed method not only achieves competitive performance several state-of-the-art methods, but also outperforms other deep learning methods in terms of model scale and computational cost.

Index Terms— Compressed sensing MRI, MRI reconstruction, convolutional neural network

1. INTRODUCTION

Magnetic resonance imaging (MRI) is an essential medical imaging technology in current clinical diagnostics to reveal the internal anatomical structures and physiological functions by a non-invasive way. Although MRI is superior in both soft-tissue contrast and resolution compared to other medical imaging modalities, the sampling process in \( k \)-space suffers from prolonged acquisition time due to physiological and hardware constraints, which discomforts patients and leads to possible motion artifacts. These limitations make MRI unsuitable for time-critical diagnostics, such as stroke. As a result, efficient reconstruction algorithms for accelerating MR imaging are urgently needed.

Over the past years, various efforts have been made to develop advanced reconstruction methods to reduce the acquisition time. These methods fall into two categories: one is hardware-based parallel MRI (pMRI) [1] which utilizes phased array coils which contain multiple independent receiver channels [2] and individual sensitivity for each coil to gain the raw data. The other one is based on the compressed sensing (CS) [3] theory, called compressed sensing magnetic resonance imaging(CS-MRI) [4, 5], which formulates specific prior information as regularization terms into iterative framework. Typical methods include total variation, low-rank and dictionary learning [6]. However, these methods suffer from heavy computational burden and tedious procedure of parameter adjustment.

Recently, the deep learning (DL) based MRI reconstruction has drawn much attention and some pioneering works have been emerged [7-15]. These methods can be roughly divided into four categories based on the different processing pipelines as shown in Fig.1. Especially, the methods represented as in Fig.1(d), which leverage both \( k \)-space and spatial prior knowledge, have demonstrated encouraging results compared with the single-domain based methods[7-13]. However, current dual-domain methods process the frequency and spatial domain data sequentially and this operation implicitly adds a certain priority priori into the reconstruction, which may ignore the internal interplay between both domains[14, 15]. To conquer this problem, we propose a novel dual-domain convolutional neural network (CNN), which contains two parallel and interactive branches simultaneously performing on \( k \)-space and spatial-domain data, dubbed as FusionNet.

The rest of this paper is organized as follows. The proposed method is elaborated in Section 2. The experimental results are shown in Section 3. The final section concludes this paper.

Fig.1 DL-based methods for fast MRI. (a) spatial-domain based methods, (b) \( k \)-space based methods, (c) directly mapping from \( k \)-space to image, (d) cross-domain reconstruction. CNN: convolutional neural network, IFT: Inverse Fourier Transform.
2. METHOD

2.1 CS-MRI

In general, the problem of MRI imaging can be approxima-
tively viewed as a linear system which is formulated as:

\[ y = F_u x + \epsilon \]  

(1)

in which \( F_u \) denotes the undersampling Fourier encoding
matrix, \( y \in \mathbb{C}^{m \times n} \) is the undersampled measurements, \( x \in \mathbb{C}^{m \times n} \) is the target image we want to reconstruct and \( \epsilon \) is the acquisition noise.

The purpose of MRI reconstruction is to recover \( x \) by
solving the inverse problem denoted by (1). To solve this ill-
posed problem, classic model-based CS-MRI [4, 5] con-
straints this problem by exploiting specific prior information,
and then the solution of (1) can be represented:

\[
\min_x \frac{1}{2} \| F_u x - y \|^2 + \lambda R(x)
\]  

(2)

where the first term is the data fidelity term, the second term
denotes the regularization term and \( \lambda \geq 0 \) is a balance factor. Typical regularization terms include TV, low-rank and dictionary learning. Recently, different neural networks are also
trained as the regularization terms.

2.2 The Proposed Method

The detailed architecture of the proposed FusionNet is illus-
trated in Fig. 2. The overall architecture is given in Fig. 2(a).
The FusionNet consists of five basic processing blocks and
all blocks share the same CNN structure except for the last
block. The network takes the undersampling \( k\)-space \( y \) and
the zero-filling reconstruction \( x_u \) as input, and predicts the
full-sampled reconstruction \( x \).
The structure of basic processing blocks are illustrated in Fig. 2(b) and (c). The first four blocks share the same structure which is shown in Fig. 2(b) and play the role of artifact reduction and detail recovery. Each block accepts two inputs: k-space and spatial-domain data, and contains two parallel and interactive branches, one for k-space data and the other for spatial-domain data. At first, both inputs from two different domains are processed by a residual block, whose structure is demonstrated in Fig. 2(d). Each residual block has 5 convolutional layers and the numbers of filters are successively set to 32, 32, 32, 32 and 2. Since MR image is usually complexed valued, we utilize two channels to respectively represent the real and imaginary parts. All kernel sizes are set to $3 \times 3$ and LeakyRelu is used as activation function following each convolutional layer. The stride is set to 1 and in order to maintain the consistency of the input and output dimensions, we set $\text{padding}=1$. K-space data consistency (KDC) and spatial data consistency (SDC) modules denote the data consistency layers. KDC follows[6] and can be calculated as:

$$s_{\text{rec}}(j) = \begin{cases} \hat{y}(j) & \text{if } j \notin \Omega \\ \frac{\hat{y} + ay(j)}{1 + \lambda} & \text{if } j \in \Omega \end{cases}$$

where $\hat{y}$ is the intermediate k-space data in the network, $\Omega$ is the sampling index set and $\lambda$ is a hyperparameter. SDC is similar with KDC and the only difference is that Fourier transform (FT) and inverse Fourier transform (IFT) are needed before and after performing (3). KF and SF are the k-space and spatial data fusion layers respectively, and are formulated as:

$$A = \frac{1}{1 + \beta} a_1 + \frac{\beta}{1 + \beta} a_2$$

where $a_1$ and $a_2$ are the inputs from same domain. The last block is similar with the previous one and the difference occurs after residual block. Since this block is responsible for outputting the final reconstructed image which is spatial instead of dual domain results, we adapt the block structure as illustrated in the Fig. 2(c). The output of KDC after IFT is directly fed into the final SF layer and combines with the output of SDC to produce the final reconstructed image.

3. EXPERIMENT RESULTS

3.1 Dataset and Training Details

We use the public brain MR raw data set—Calgary-Campanas dataset(https://sites.google.com/view/calgary-campanas-dataset/home/mr-reconstruction-challenge), which comes from the clinic MR scanner (Discovery MR750; General Electric (GE) Healthcare, Waukesha, WI), to train and test our model. The training set contains 4524 slices from 25 subjects, and the testing set contains 1700 slices from 10 subjects. The acquisition matrix size is $256 \times 256$.

Adam was chosen as the optimizer and the parameters $\ell r = 5e^{-5}$, $\beta_1 = 0.9$ and $\beta_2 = 0.999$. The MSE loss was used as the loss function. $\lambda$ and $\beta$ in (3) and (4) were trained in the network. The proposed model was implemented with PyTorch framework and trained on a workstation equipped with one GPU (GTX 1080 Ti).

To evaluate the performance of the proposed method, we compared our method with three state-of-the-art methods including PANO [16], DIMENSION [15], and ADMM-CSNet [12]. PANO is a classical CS-MRI method. ADMM-CSNet is an unrolled iteration network, which have shown powerful performance. DIMENSION is a recently published dual-domain reconstruction method. Peak signal to noise ratio (PSNR) and structural similarity index measure (SSIM) were employed as the quantitative metrics.

3.2 Comparison to The State-of-the-art Methods

In order to validate the visual performance of the proposed FusionNet compared with other methods. The results with radial sampling patterns with 10% and 20%, and cartesian sampling pattern with 25% sampling rate are included. The results and error maps reconstructed by different methods are shown in Fig. 3. In Fig. 3, it can be seen that all methods are able to achieve good de-aliasing results. As shown by the error maps, the proposed FusionNet resulted in the lowest overall error and maintained more fine details in all the sampling cases, owing to the proposed dual-domain data recovery and consistency blocks.

The average quantitative results of different methods are shown in Table 1. The dual-domain methods achieved better performance than the classical CS-based and single-domain network based reconstruction methods. It can be noticed that the proposed FusionNet obtained best scores, which can be treated as an adamant evidence of good generalization ability at different sampling patterns and rates for our method. Parts of the scores of DIMENSION are close to our method, but DIMENSION only processes the k-space data successively in k-space and spatial domains once and no interaction between both domains are involved.

As we know, the complexity of the DL-based method is also an important evaluation factor. Here we compared the complexity of the DIMENSION and FusionNet in terms of amount of parameters and floating point operations per second (FLOPS). The amounts of parameters of DIMENSION and FusionNet are 848010 and 289319, and the FLOPs are

| Method       | Cartesian 20% | Radial 10% | Radial 20% |
|--------------|---------------|------------|------------|
| Zero-filling | 18.55±0.82    | 18.79±0.80 | 18.85±0.94 |
| PANO         | 0.57±0.05     | 0.51±0.03  | 0.57±0.03  |
| ADMM-CSNet   | 30.46±2.11    | 35.67±1.75 | 35.44±1.71 |
| DIMENSION    | 31.13±1.86    | 36.21±2.26 | 36.05±2.29 |
| FusionNet    | 32.00±1.38    | 32.92±1.50 | 38.26±1.35 |
|              | 0.90±0.02     | 0.91±0.02  | 0.96±0.01  |


4. CONCLUSION

In conclusion, we developed a novel neural network for fast magnetic resonance imaging. The proposed network consists of two parallel interactive branches respectively acting on $k$-space and spatial data. The experimental results show that our method is robust to different sampling patterns and rates, and can efficiently suppress the artifacts while preserving more details and has lower complexity. Future works will focus on a more systematic comparison and analysis on different sampling strategies, scanning protocols and clinical scenarios.

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