Deep Learning Approach for Spiral Parallel Imaging Reconstruction

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Abstract

A deep learning based iterative reconstruction method imaging is proposed for spiral parallel imaging, and a tensorflow-supported operator for non-uniform fast Fourier transform is introduced. Instead of regarding the reconstruction problem as a single estimation from least-squares, a ResNet-like network is placed before the implementation of conjugate gradient algorithm functions as a denoiser. In our experiments, the proposed framework demonstrates high performance over conventional methods using precondition iterative algorithm.

Keywords: Deep learning, ResNet, MR image reconstruction, spiral imaging, iterative reconstruction.

1. Introduction

The application of multiple receiver coils in MR imaging is common in clinical practice to shorten scanning time (Blaimer et al., 2004). With the spatial information provided by coil sensitivity, parallel imaging permits the reduction of gradient coding line without lowering image quality dramatically. There has been some research about the implementation of parallel imaging with non-cartesian sampling trajectory (spiral, radial) (Griswold et al., 2002). The image reconstruction of non-cartesian k-space data is achieved by solving a least square problem with precondition conjugate gradient algorithm in Ref (Pruessmann et al., 2001).

2. Proposed method

According to the study of coil sensitivity-based image reconstruction from multiple coil data in Ref (Pruessmann et al., 1999), the reconstruction can be formulated as following:

\[ Ew_x + n = d_k \] (1)

where \( E \) denotes the encoding matrix comprised of several operators \([G_{k,t} \ F_{x \rightarrow k} \ S]\), \( G_{k,t} \) represents the gridding operation in k-space, \( F_{x \rightarrow k} \) contains Fourier basis corresponding to forward Fourier transformation, \( S \) is the complex spatial sensitivity of each coil, \( w_x \in \mathbb{R}^n \) is the image to be reconstructed from incomplete observations \( d_k \in \mathbb{C}^m (m < n) \) and
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\[ n \in \mathbb{C}^m \] is sampling noise. \( G_{k,t} \) and \( F_{x \rightarrow k} \) can be merged into a non-uniform fast Fourier transform (NUFFT) operator. It should be noted that the singularity of encoding matrix \( E \) make Eq. (1) to be ill-posed, which means the precondition methods used in conjugate gradient converges to an optimized restored image which is close to desired image but still has image quality loss. The objective of proposed reconstruction methods is to reduce the loss between optimized image and the desired image and keep consistency with the measured data.

2.1. Reconstruction Network

The proposed model consists of two parts: the first part denoises the initial image, the second part take the denoised image as initial point for conjugate gradient algorithm as shown in Fig. 1a. In this way, the stacked convolution layers provide a better initial point or a feasible solution search path for the conjugate gradient loop. And complex images are fed into network via real and imaginary channels.

![An illustration of proposed framework](a) An illustration of proposed framework  (b) Back-propagation for FFT

Figure 1: Network structure

Given an training dataset, the loss function between the network reconstruction output and the ground-truth is defined as:

\[
E(\Theta) = \sum_{N} \| \Gamma(d_k, \Theta) - w^*_x \|^2
\]

where \( \Gamma(d_k, \Theta) \) is the network output with parameter \( \Theta \) and undersampling data \( d_k \) in k-space, \( w^*_x \) denotes the corresponding ground-truth image.

2.2. Non-uniform FFT operator

The forward Fourier transformation of \( x \) can be presented by a multiplication with DFT matrix \( W \) which are expressed as following:

\[
W = \left( \frac{\omega^{jk}}{\sqrt{N}} \right)_{j,k=0,\ldots,N-1}, \quad w = e^{-2\pi n/N}
\]

\[
f = W \cdot x
\]
So the Jacobian of forward fast Fourier transformation (FFT) is given by:

\[
\frac{\partial f}{\partial x} = W \rightarrow \Delta y = W \Delta x \rightarrow \Delta x = W^{-1} \Delta y
\]

where \( W \) is unitary matrix whose inverse equals its transpose. The non-uniform FFT is the same as FFT in term of gradient back-propagation which is shown in Fig. 1b.

### 2.3. Training

We use bart toolbox to generate coil sensitivity maps and use mini-time acquisition to design spiral sampling trajectory with time-optimal gradient waveform (Tamir et al., 2016; Lustig et al., 2008). The full-sampling scheme is comprised of 12 shots. With 4-fold undersampling, a training case consists of an initial image from 3 shots and a full-sampling image. We use 360 training case and train the network for 100 epochs.

### 3. Result

We test and compare the reconstruction performance of conventional method and proposed method. The quantitative comparison explicitly shows that the proposed framework achieves 43.22 dB, 5.17 dB higher than conventional reconstruction method.

![Figure 2: Qualitative comparison on T1-weighted image reconstruction with 4-fold undersampling](image)

(a) Conventional(38.05) (b) Proposed(43.22) (c) Ground truth(PSNR)

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### References


