Partial-Fourier Reconstruction for Functional MRI(fMRI) using Deep Learning

Seul Lee
Electrical Engineering
seul@stanford.edu

Abstract

Partial Fourier reconstruction is well-known MR reconstruction that acquires half number of k-space data using Hermitian symmetry [1]. I suggested a new method for Partial Fourier reconstruction (Even/Odd) that is more robust to off-resonance, which is critical in functional MRI (fMRI), compared to the existing method. In this new reconstruction, neighboring voxels can be used to compensate for missing voxels since it has every other lines in k-space. In this project, I applied deep learning algorithm to fill the missing k-space lines and evaluated. After training data, missing k-space lines were filled with the predicted values and reconstructed. Trained data reconstructed images successfully compared to the images from the fully sampled data and Mean Squared Error (MSE) is 0.038-0.048 and 0.317-0.319 for magnitude and phase, respectively.

1. Introduction

In Magnetic Resonance Imaging (MRI), we acquire the signal in frequency domain (k-space) and apply Fourier transform to reconstruct images. To reduce scan time, Partial Fourier reconstruction that acquires partial number of k-space data is widely used and reconstruct images using Hermitian symmetry. One of the well-known methods for partial Fourier acquisition is homodyne [1]. It acquires one half of k-space and a few additional data in the other half to provide a low frequency phase image for correction. In functional MRI (fMRI), altered magnetic susceptibility near air/tissue interfaces in the brain causes magnetic field inhomogeneity that results in off-resonance. Homodyne reconstruction, however, is vulnerable to off-resonance. As most of the energy is at the center of k-space, homodyne acquisition can cause loss of signal when there is a magnetic gradient shift. Figure 1-a and b show acquired k-space data and reconstructed brain image using homodyne. In this dataset, there is a linear shift in phase encoding (horizontal) direction and the peak is shifted and most of the energy is lost (Fig. 1-a). Therefore, large attenuations occur in the reconstructed image (Fig.1-b).

2. Related work

I proposed a new method for partial Fourier, Even/Odd (E/O) method in previous work (in review). E/O method acquires only even-numbered k-space lines in half and odd-numbered k-space lines in the other half of k-space. As it acquires the same number of k-space data as homodyne, it reduces the scan time but does not result in a sharp boundary near the k-space origin. Figure 1-c and d show acquired k-space data and reconstructed brain image using E/O method. Even though there is a shift in k-space data, the reconstructed brain image does not have much attenuation (Fig.1- c and d) since every other lines are acquired and it does not lose as much data as homodyne.

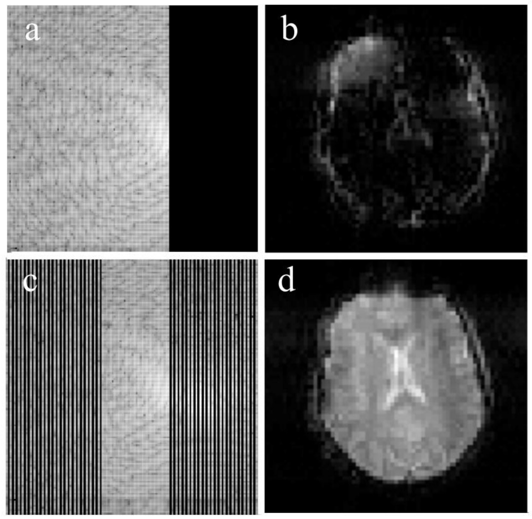

Figure 1. Concepts of partial Fourier acquisition are shown. a) Acquired k-space data using homodyne acquisition, b) reconstructed image using homodyne acquisition, c) acquired k-space data using E/O acquisition, and d) reconstructed image using E/O acquisition. k-Space data (a and c) are shown in log scale.

In the case of E/O method, missing lines can be filled with values using neighboring lines because E/O acquires every other lines in k-space. In this project, I will apply deep learning method to fill these missing k-space lines to reconstruct brain images.

3. Dataset and Features

Dataset

The fMRI data were acquired at 3T GE scanner at Lucas center with TR/TE = 2100/20 ms, 3.4 mm resolution and 4 mm slice thickness. k-Space data consists of 64 × 64 in a slice (z) direction, 30 slices. Out of 64 columns in a plane, 12 lines out of 24 lines from left half and same numbers of lines from right half and 17 lines at the center. I have used 64 × 41 × 30 × 3 k-space points for training and 64 × 41 points for test.

For E/O method, I zeroed out k-space lines from fully acquired data and made them into one column data. There are left value and right value in one row (e.g. k-space value at (2, 2) position and k-space value at (2, 4) position) (Fig. 2). These columnized data are the input features, and values between two points are output labels to train. Input features have (2, 138,240) which 2 came from X_{11}, X_{12} (first row, for example) and 138,240 came from 64 × 41 × 30 × 3. Input features start with first row (1st column, 3rd column) pair and second row (3rd column and 5th column pair and so on. Labels start with first row (2nd column) and second row (4th column) and so on.

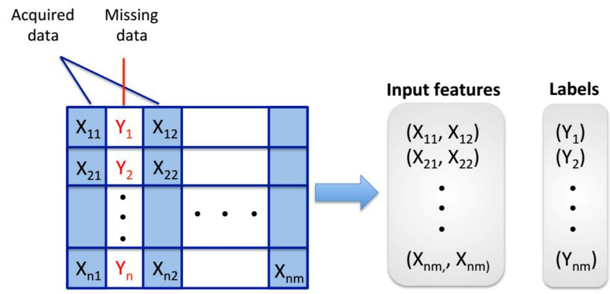

Figure 2. Data structure. Acquired data are shown in blue and missing data are shown in white. The k-space values at blue position are input features and the values at white position are labels. n = 2, m = 138,240 in X_{nm} and n = 1, m = 138,240 in Y_{nm}.

Pre-processing

To simulate E/O method, I zeroed out every other lines from both k-space and kept the lines at the center using MATLAB. Out of 64 lines, 12 even-numbered lines from one half, 12 odd-numbered lines from the other half and 17 full lines at the center were remained after zeroing out. The data were normalized before training. As described in Dataset, 2D data converted to one column data. Since the data consists of magnitude and phase components, I trained/tested them separately.

Features/Labels

k-Space values at acquired voxels are features and the values at missing voxels are labels. The row of the features is two position values in k-space and the column of the features is the number of datasets.

4. Methods

I applied Linear-Relu/tanh-Linear-Relu/tanh-Linear algorithm to compensate missing k-space data (Fig. 3). Relu activation function was used for magnitude as the magnitude has values of 0-some large numbers (every slice has different maximum nuber) and tanh activation function was used for phase as the phase has values of –pi to +pi. To reduce cost, gradient descent optimizer was applied.

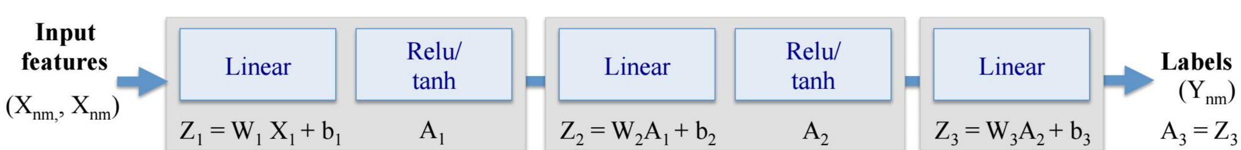

Figure 3. Model structure. n = 2, m =138,240 in X_{nm} and n = 1, m = 138,240 in Y_{nm}.

5. Results

Post-processing

After training/testing the data, those predicted labels were filled in the original position in k-space. IFFT was applied to reconstruct brain images.

Evaluation

Reconstructed images after filling missing k-space data using the algorithm is compared to the reconstructed images from fully sampled data (Fig. 4). Mean Squared Error (MSE) between labels and predictions to evaluate the algorithm. Training datasets have 138,240 positions (samples) and MSE for magnitude is 0.038, MSE for phase is 0.317. Test datasets have 1,536 positions (samples) and MSE for magnitude is 0.048, MSE for phase is 0.319 (Table 1).

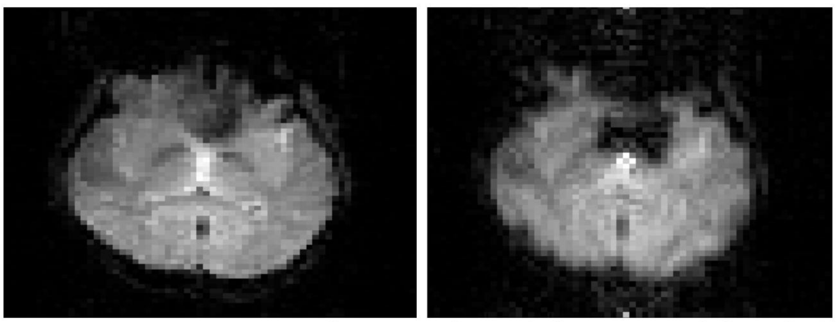

Figure 4. Reconstructed images from fully acquired data(left) and tested data(right)

	Training	**Test**
Dataset	138,240 positions	1,536 positions
MSE	0.038 (mag) 0.317 (phs)	0.048 (mag) 0.319 (phs)

Table 1. Number of samples, MSE for training/test datasets are shown.

6. Discussion/Future works

It is well known that Partial Fourier acquisition reconstructs MR images well and some deep learning algorithms were used to reconstruct Partially acquired MR data with existing method (Homodyne). I suggested new Partial Fourier method and methods for compensating missing data in previous research and the method that I showed in this project is one of the other methods to fill the missing data. Since neighboring voxels are correlated in MR images, they can be used to compensate missing k-space data in E/O reconstruction. In this project, the missing voxels were filled using deep learning algorithm.

In the future, I can apply deep learning algorithms to end-to-end application: making full k-space images as input features and reconstructed images as output images using convolutional neural network (CNN).

Acknowledgement

Thanks to my project TA Brandon Chauloon Yang and Gary Glover for helpful discussion and comments.

Reference

[1] Noll DC, Nishimura DG, Macovski A. Homodyne detection in magnetic resonance imaging. IEEE Trans Med Imaging 1991;10(2):154-63.