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

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Predicting

Functional Magnetic Resonance Imaging (fMRI) is an MRI method for looking at brain functional connectivity by detecting blood flow changes. To reduce scan time, Partial Fourier reconstruction that acquires partial number of k-space data is widely used and reconstruct images using Hermitian symmetry. We proposed new Partial Fourier reconstruction method in other research: Even/Odd (E/O) reconstruction. In this method, as there are every other lines in k-space, the missing voxels can be filled using nearby voxels. In this project, I used deep learning algorithm to compensate missing k-space voxels by training nearby voxels.

Data

Data acquisition

- 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 × number of planes in slice (z) direction (64 × 64 matrices in plane).
- Number of rows = 64, number of columns = 41/64, number of slice = 30

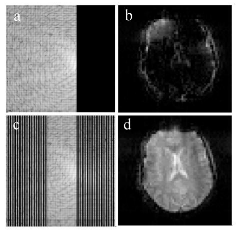


Figure 1. Concepts of partial Fourier acquisition: Homodyne [1] (a,b), E/O (c,d)

Preprocessing

- FFT was applied to transform between k-space and images
- Magnitude/phase were separated and normalized
- Zero-out every other lines from each half keeping the center lines

Features/Labels

- **Features**: k-space values at acquired voxels
- **Labels**: the values at missing voxels
- Row: two position values in k-space,
- Column: number of datasets (each point in k-space)

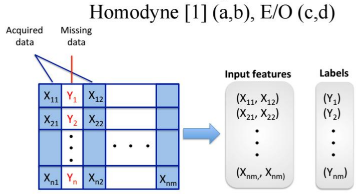
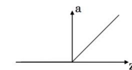


Figure 2. Data structure

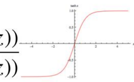
Models

Models

- Motivation: Filling missing lines using neighboring voxels works well
- **Linear-tanh-inear-tanh-inear-tanh** model is applied
- Activation functions: **relu** for magnitude and **tanh** for phase
- Linear: $Z_i = W_i X_i + b_i$, Relu: $G(Z_i) = \max(0, Z_i)$, $\tanh(z) = \dfrac{(\exp(z) - \exp(-z))}{(\exp(z) + \exp(-z))}$
- W1: [16, 2], W2: [8, 16], W3: [1, 8]



Relu activation



tanh activation

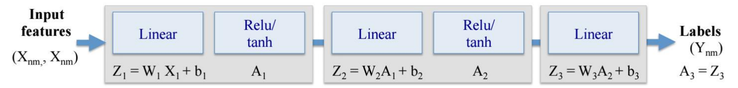


Figure 3. Model structure. n = 2, m =236160 in X_{nm} and Y_{nm}

Optimization

- Gradient descent optimizer

Results

Post-processing

- Obtained data were filled in the original position in k-space
- IFFT was applied to reconstruct brain images

(a) Fully sampled (b) Prediction

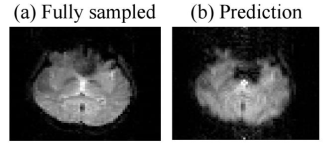


Figure 4. Reconstructed images from fully acquired data (a) and tested data(b)

Evaluation

- Mean Squared Error (MSE) between labels and predictions

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

Discussion

- 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, instead of point to point learning, CNN can be used for training whole k-space to reconstructed images, which is an end-to-end application.

Acknowledgement

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References

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