Introduction

• Under-sampled reconstruction in resting-state fMRI holds the potential to enable higher spatial resolution in brain R-fMRI without increasing scan duration.
• We propose a novel convolutional neural network (CNN) framework to reconstruct R-fMRI from k-t under-sampled data.
• The CNN framework for reconstruction comprises of two jointly-learned multi-layer CNN components for i. explicitly filling in missing k-space data, using acquired data in frequency-temporal neighborhoods, and ii. image quality enhancement in the spatiotemporal domain.
• Results show improvements over the state of the art in the connectivity maps for three cerebral functional networks.

Methods

Model Variations

<table>
<thead>
<tr>
<th>Model</th>
<th>Layers (Φ &amp; Ψ)</th>
<th>Loss</th>
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<tbody>
<tr>
<td>S-CNN</td>
<td>2</td>
<td>Mean squared</td>
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<tr>
<td>D-CNN</td>
<td>4</td>
<td>Mean squared</td>
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<tr>
<td>RD-CNN</td>
<td>4</td>
<td>Robust</td>
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<td>BD-CNN</td>
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<td>Bayesian</td>
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Baselines

- RA-DICT: A robust data-adaptive sparse dictionary model
- WAVE: A sparse wavelet model on the spatiotemporal fMRI signal
- LOWRANK: Low-rank model on the joint k-space and temporal domain
- BDMRT-T: Adaption of a CNN-based dynamic-MRI reconstruction method

Results on R-fMRI Data from Human Connectome Project

Quantitative Results on Brain R-fMRI: Comparison of all methods, through mSSIM boxplots over 50 evaluation-set subjects and all functional-networks.

Insensitivity to Choice of Training and Validation Sets

mSSIM Boxplots, over 50 evaluation set subjects and all functional networks, for BD-CNN learned from 5 different training and validation sets.

Ablation Studies

Performance for Different Values of Free-Parameter λ

• Trend: Performance deteriorates significantly as λ → 1.
• Average mSSIM (and standard deviation across all functional networks and evaluation subjects) for λ ∈ [0.7, 0.8] is 0.90 (0.03), and for λ = 1 is 0.88 (0.03); demonstrates utility of third stage of our architecture.
• We set λ = 0.5 because it leads to reduced training time in practice.

Effect of Head Motion

• We simulate head motion for each subject during the 15-minute scan that rotates the head about the spine every minute.
• We choose the rotation angle to generate realistic head motion, and add noise.
• The average mSSIM (and standard deviation) over all functional networks and evaluation subjects is (i) BD-CNN: 0.90(0.04), (ii) BD-CNN-T: 0.87(0.05), (iii) RA-DICT: 0.86(0.06), (iv) WAVE: 0.86 (0.02), and (v) LOWRANK: are 0.79 (0.04).

Uncertainty of Reconstruction in Cerebral BOLD Signals

• We can treat the BD-CNN output standard-deviation values as estimates of the relative uncertainty, between voxels, in the reconstructed intensities.
• The artifacts introduced due to k-space under-sampling of the original data are clearly seen in the residuals.
• The corresponding per-voxel standard-deviation maps show higher values (i.e. higher uncertainty) with spatial patterns similar to those in residuals.

Overview

• Subsampling scheme subsamples both in time and k-space; and acquisition noise is also added.
• The CNN architecture, with end-to-end learning, has stage (1) that uses a CNN to fill in missing k-space data using acquired data in k-t neighborhoods, and (2) that includes a Fourier inverse to transform the data to the spatial domain, and (3) that uses a CNN learned for image quality enhancement in the spatiotemporal domain.