A Bayesian Deep CNN Framework for Reconstructing k-t Under-sampled Resting-fMRI

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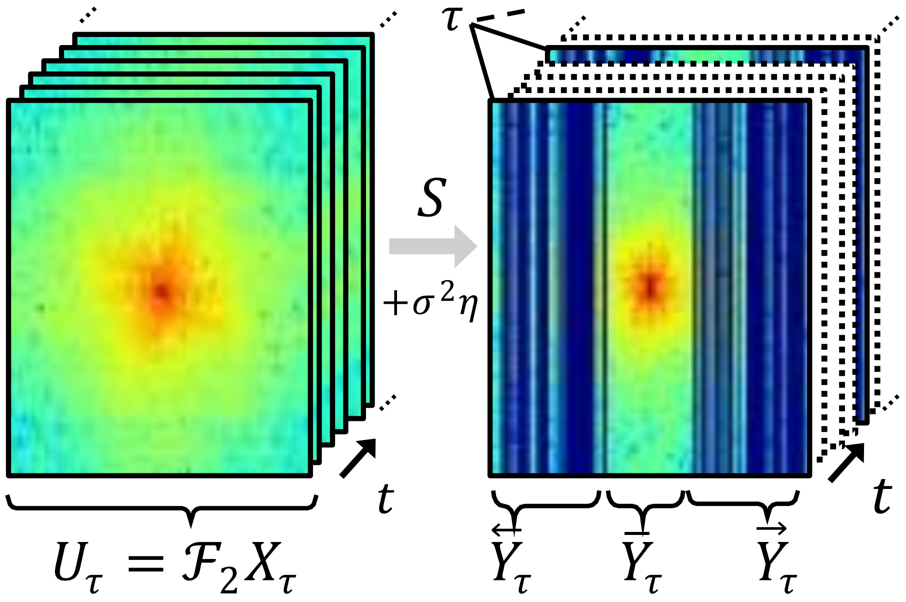
Introduction

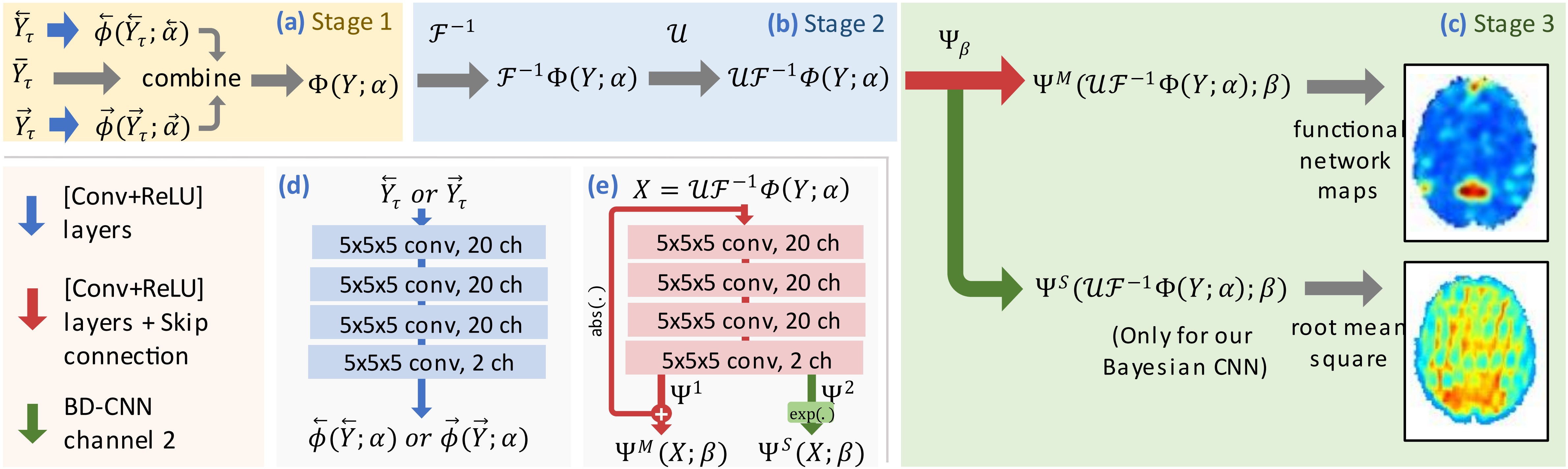
- Under-sampled reconstruction in resting-state fMRI holds the potential to enable higher spatial resolution in brain R-fMRI without increasing scan duration.
- We propose a novel convolutional neural network (CNN) framework to reconstruct R-fMRI from k-t under-sampled data.
- The CNN framework for reconstruction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

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,
  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.



Model



(a) Stage 1
combine
(b) Stage 2
(c) Stage 3
functional network maps
root mean square
(Only for our Bayesian CNN)
[Conv+ReLU] layers
[Conv+ReLU] layers + Skip connection
BD-CNN channel 2
(d)
5x5x5 conv, 20 ch
5x5x5 conv, 20 ch
5x5x5 conv, 20 ch
5x5x5 conv, 2 ch
(e)
5x5x5 conv, 20 ch
5x5x5 conv, 20 ch
5x5x5 conv, 20 ch
5x5x5 conv, 2 ch
abs(.)
exp(.)

Loss Functions

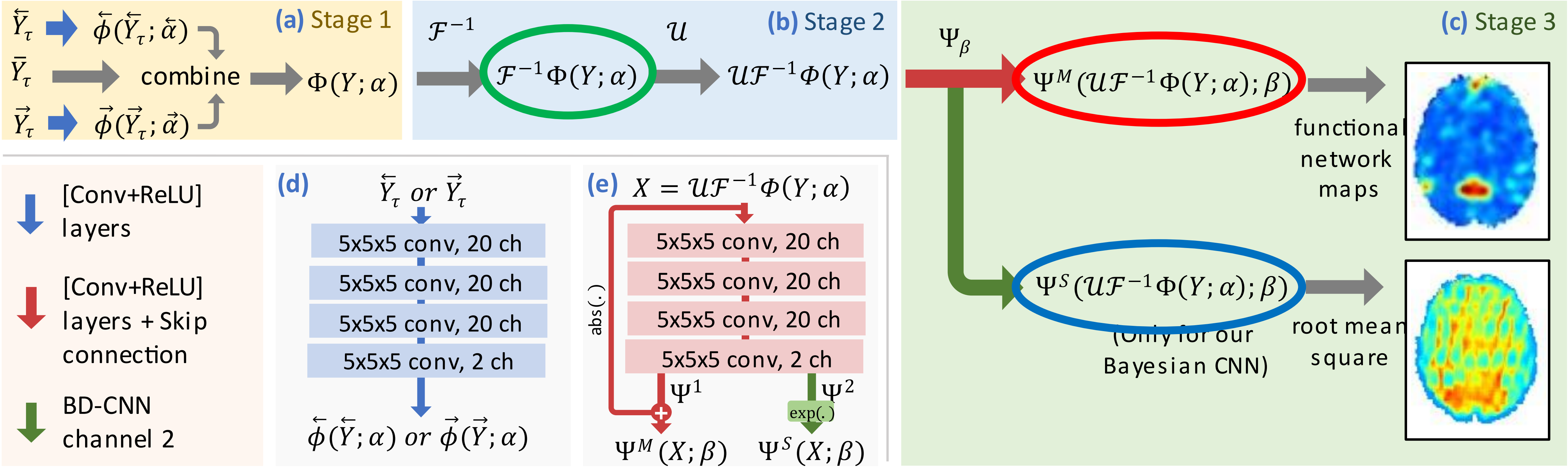
- Mean Squared Loss ($p = 2$)
- Robust Loss ($p = 0.5$)

$$\arg\min_{\alpha,\beta} (1-\lambda) \sum_n \left\| X^n - \Psi^{\mathrm{M}}(Y^n;\alpha,\beta) \right\|_2^p + \lambda \sum_n \sum_\tau \left\| X_\tau^n - \mathcal{F}^{-1}\Phi(Y_\tau^n;\alpha) \right\|_2^p$$

- Bayesian Loss

$$\arg\min_{\alpha,\beta} \sum_n \sum_v \sum_t \frac{\left(X_{vt}^n - \Psi_{vt}^M(Y^n;\alpha,\beta)\right)^2}{\Psi_{vt}^S(Y^n;\alpha,\beta)^2} + 2\log\left(\Psi^S(Y^n;\alpha,\beta)\right)$$

Model



(a) Stage 1
combine
$\overleftarrow{\phi}(\overleftarrow{Y}_\tau;\overleftarrow{\alpha})$
$\vec{\phi}(\vec{Y}_\tau;\vec{\alpha})$
$\Phi(Y;\alpha)$
(b) Stage 2
$\mathcal{F}^{-1}$
$\mathcal{F}^{-1}\Phi(Y;\alpha)$
$\mathcal{U}$
$\mathcal{U}\mathcal{F}^{-1}\Phi(Y;\alpha)$
(c) Stage 3
Ψ_β
$\Psi^M(\mathcal{U}\mathcal{F}^{-1}\Phi(Y;\alpha);\beta)$
functional network maps
$\Psi^S(\mathcal{U}\mathcal{F}^{-1}\Phi(Y;\alpha);\beta)$
(Only for our Bayesian CNN)
root mean square
[Conv+ReLU] layers
[Conv+ReLU] layers + Skip connection
BD-CNN channel 2
(d)
$\overleftarrow{Y}_\tau$ or $\vec{Y}_\tau$
5x5x5 conv, 20 ch
5x5x5 conv, 20 ch
5x5x5 conv, 20 ch
5x5x5 conv, 2 ch
$\overleftarrow{\phi}(\overleftarrow{Y};\alpha)$ or $\vec{\phi}(\vec{Y};\alpha)$
(e) $X = \mathcal{U}\mathcal{F}^{-1}\Phi(Y;\alpha)$
5x5x5 conv, 20 ch
5x5x5 conv, 20 ch
5x5x5 conv, 20 ch
5x5x5 conv, 2 ch
abs(.)
Ψ^1
Ψ^2
exp(.)
$\Psi^M(X;\beta)$
$\Psi^S(X;\beta)$

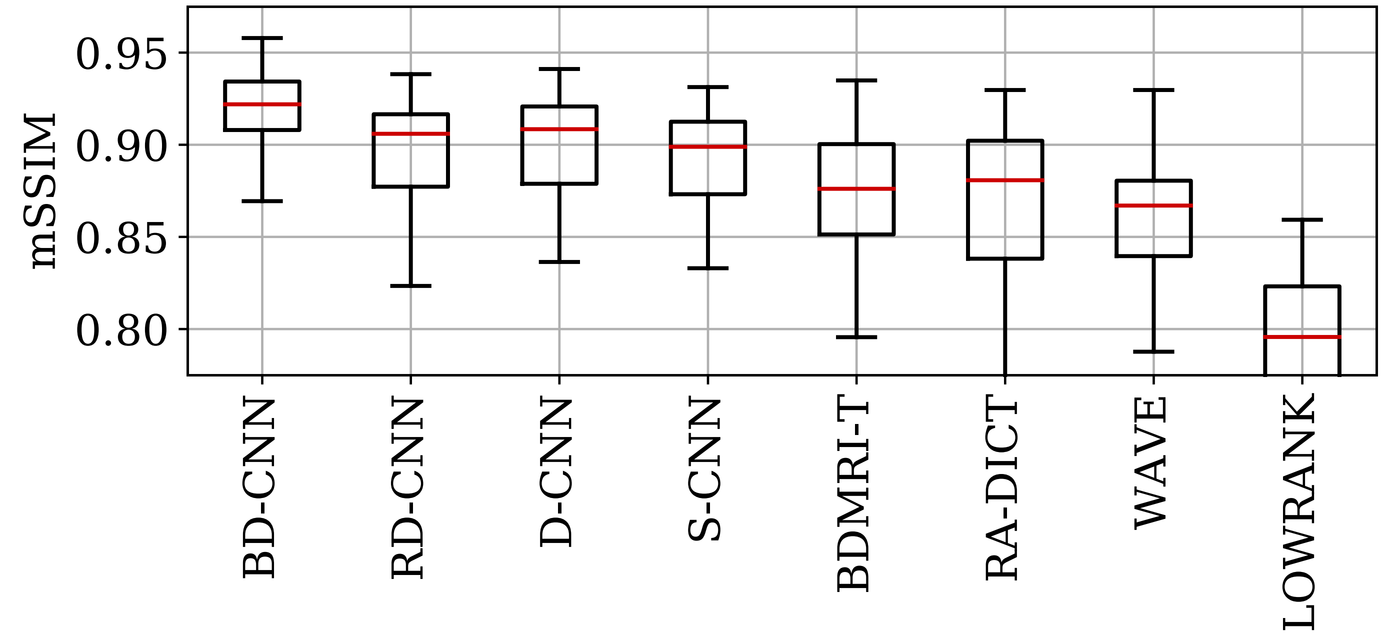
Model Variations

Model	Layers (Φ & Ψ)	Loss
S-CNN	2	Mean squared
D-CNN	4	Mean squared
RD-CNN	4	Robust
BD-CNN	4	Bayesian

Baselines

Model	Description
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
BDMRI-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.

Results on R-fMRI Data from Human Connectome Project

Qualitative Results on Brain R-fMRI

Dorsal Attentive Network (DAN) estimated from

(a) original data; from fitted models using

(b) BD-CNN: mSSIM 0.93,

(c) RD-CNN: mSSIM 0.92,

(d) D-CNN: mSSIM 0.93,

(e) S-CNN: mSSIM 0.92,

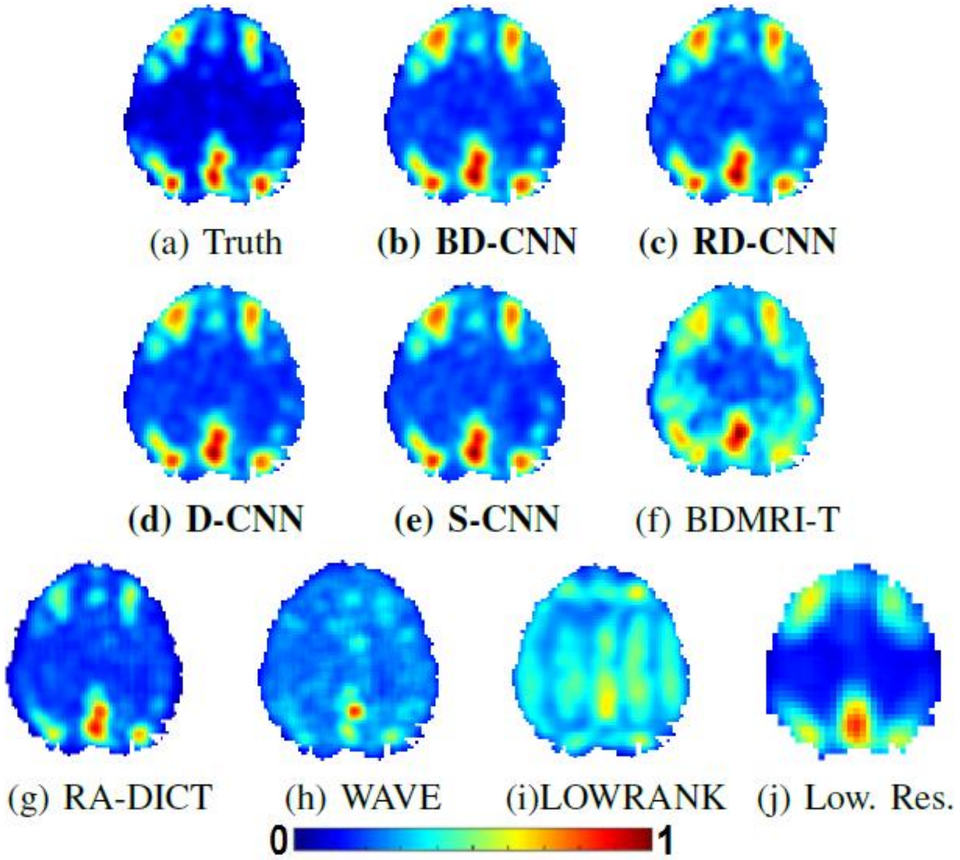
(f) BDMRI-T: mSSIM 0:85,

(g) RA-DICT: mSSIM 0:91,

(h) WAVE: mSSIM 0:85,

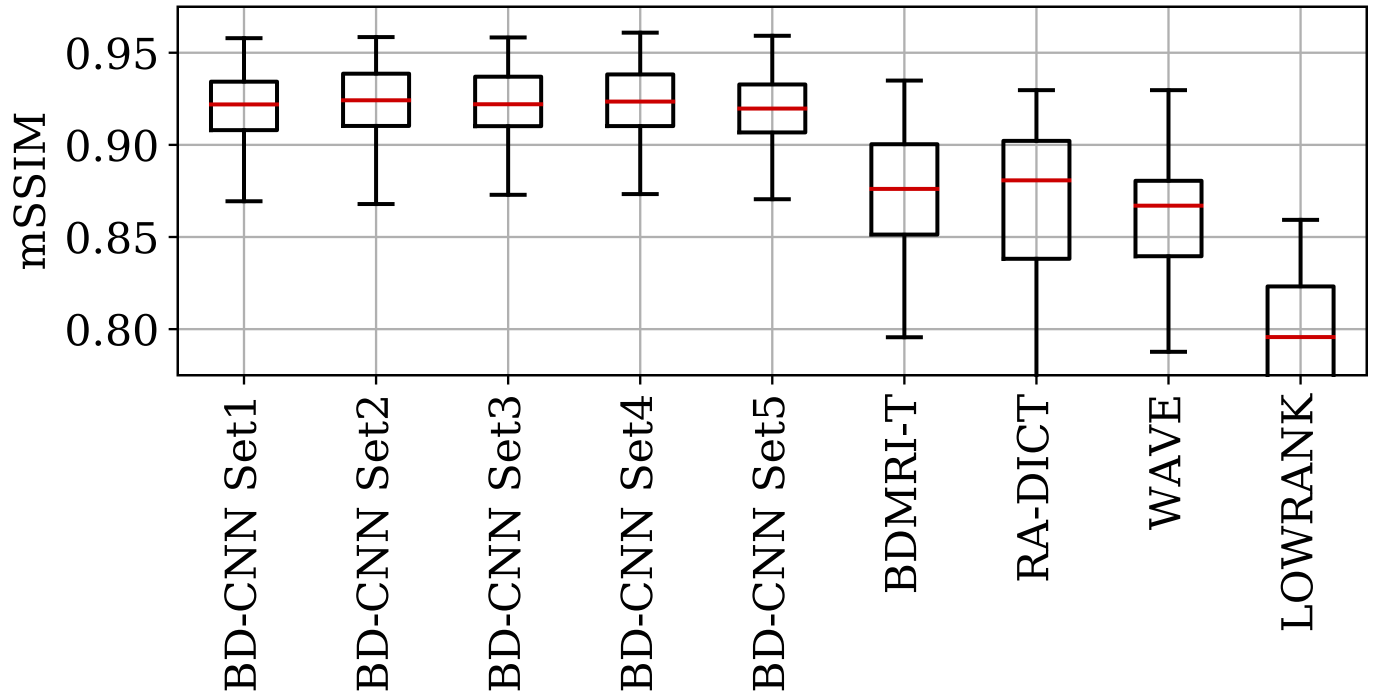
(i) LOWRANK: mSSIM 0:74; and from

(j) 8× lower spatial resolution of (a): mSSIM 0:82.



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.



Performance for
Different Values of Free-Parameter $\boldsymbol{\lambda}$

Recall: $$\arg\min_{\alpha,\beta}\,(1-\lambda)\sum_{n}\|X^n-\Psi^{\mathrm{M}}(Y^n;\alpha,\beta)\|_2^p+\lambda\sum_{n}\sum_{\tau}\|X_\tau^n-\mathcal{F}^{-1}\Phi(Y_\tau^n;\alpha)\|_2^p$$

- Trend: Performance deteriorates significantly as $\lambda \to 1^{-}$.
- Average mSSIM (and standard deviation for all functional networks and evaluation subjects) for $\lambda \in [0,0.75]$ is 0.90 (0.03), and for $\lambda = 1$ is 0.88 (0.03); demonstrates utility of third stage of our architecture.
- We set $\lambda = 0.5$ 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 are
    - **BD-CNN**: 0.90 (0.04),
    - **BDMRI-T**: 0.87 (0.05),
    - **RA-DICT**: 0.86 (0.06)
    - **WAVE**: 0.86 (0.02),
    - **LOWRANK**: are 0.79 (0.04).

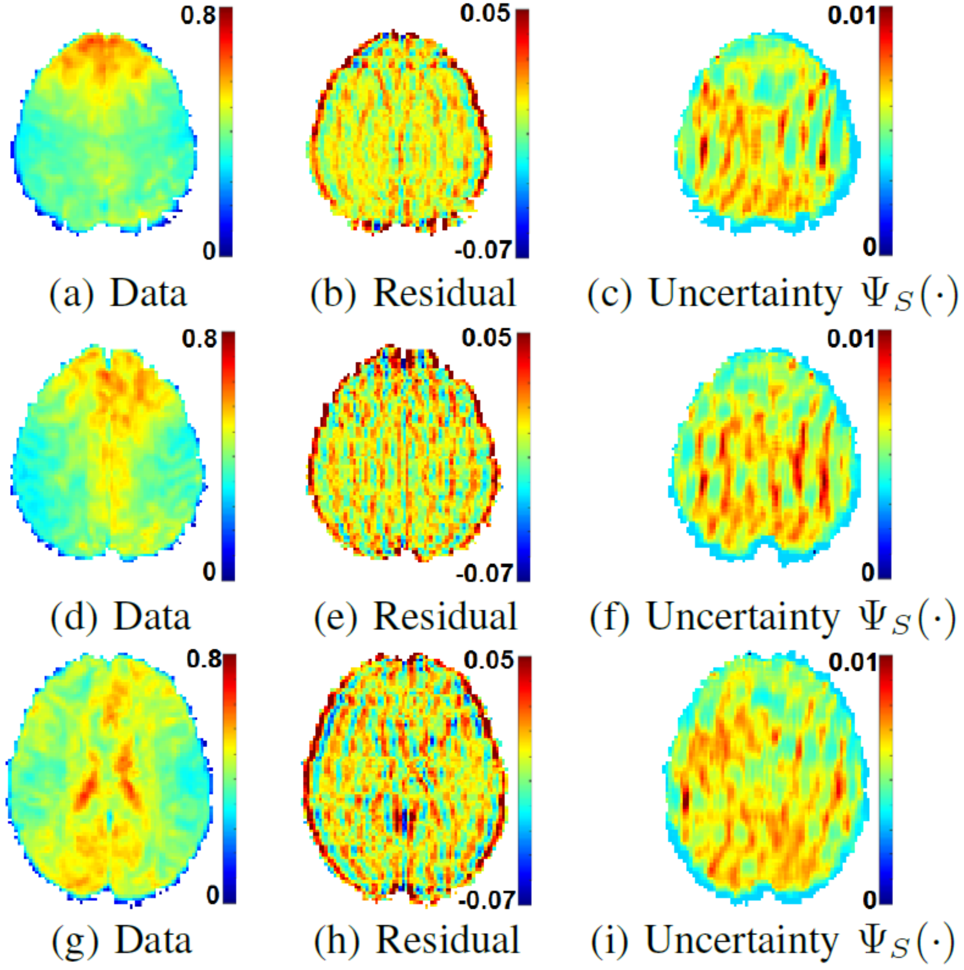
Uncertainty Maps of Reconstruction in Cerebral BOLD Signals

- We can treat the BD-CNN output standard-deviation values as estimates of the 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 a similar to those in residuals.

Uncertainty Maps of Reconstruction in Cerebral BOLD Signals

Column 1 (a, d, g) original data,
Column 2 (b, e, h) residual between original data and zero-filled reconstruction, and
Column 3 (c, f, i) per-voxel uncertainty map (standard-deviation map $\Phi^{S}(.)$) for

- DAN region (row 1),
- ECN region (row 2) and
- DMN region (Row 3).



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Presentation and recording by

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