A BAYESIAN DEEP CNN FRAMEWORK FOR RECONSTRUCTING k-t UNDERSAMPLED RESTING-fMRI

Karan Taneja [1], Prachi H. Kulkarni [1], S. N. Merchant [1], Suyash P. Awate [2]

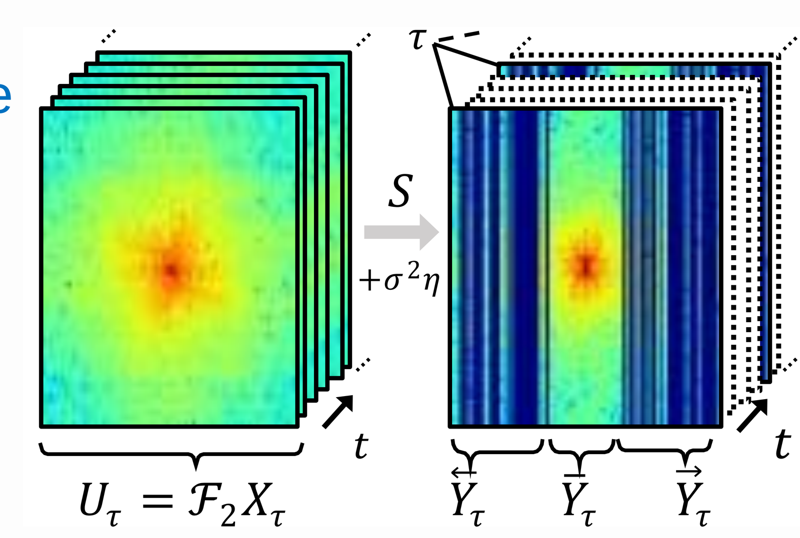
[1] Department of Electrical Engineering, Indian Institute of Technology (IIT) Bombay. [2] Department of Computer Science and Engineering, Indian Institute of Technology (IIT) Bombay.

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
  - 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.

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.

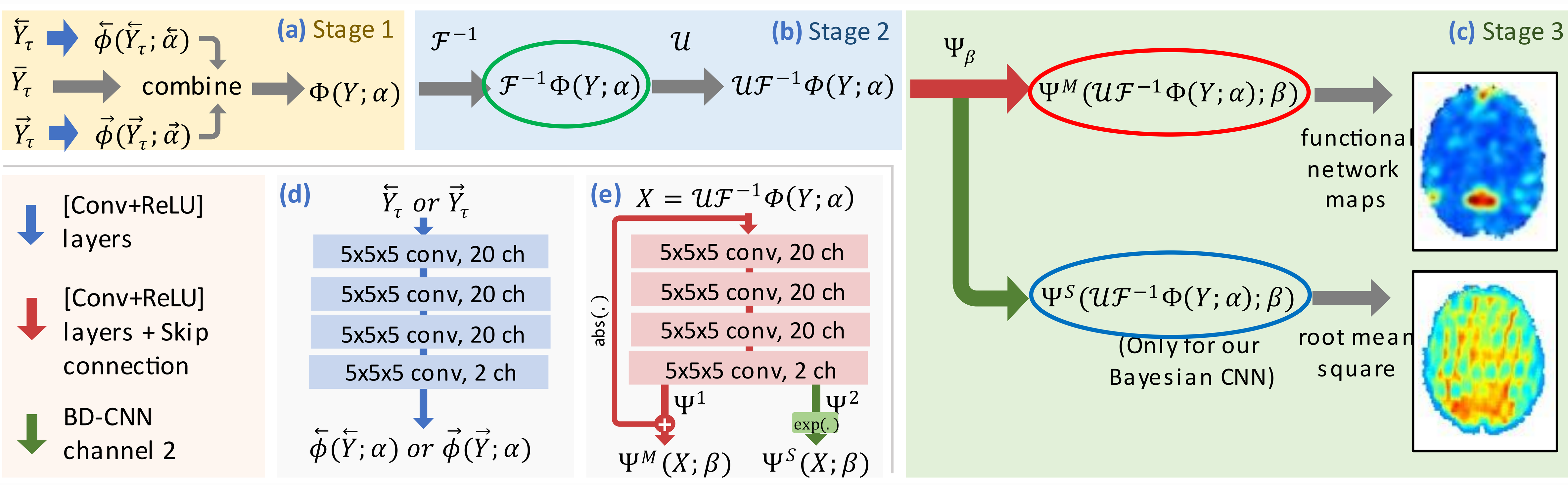
Methods

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



Mean Squared Loss ($p = 2$), Robust Loss ($p = 0.5$):

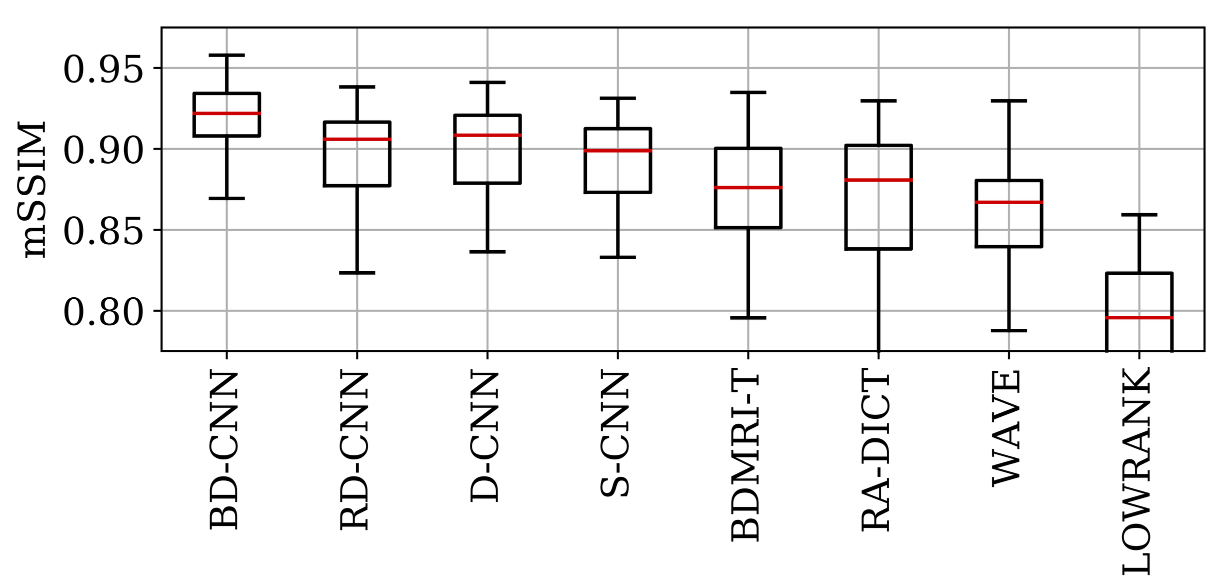
$$\arg\min_{\alpha,\beta} (1-\lambda)\sum_n \left\|X^n - \Psi^M(Y^n;\alpha,\beta)\right\|_2^p + \lambda \sum_n \sum_\tau \left\|X_\tau^n - \mathcal{F}^{-1}\Phi(Y_\tau^n;\alpha)\right\|_2^p$$

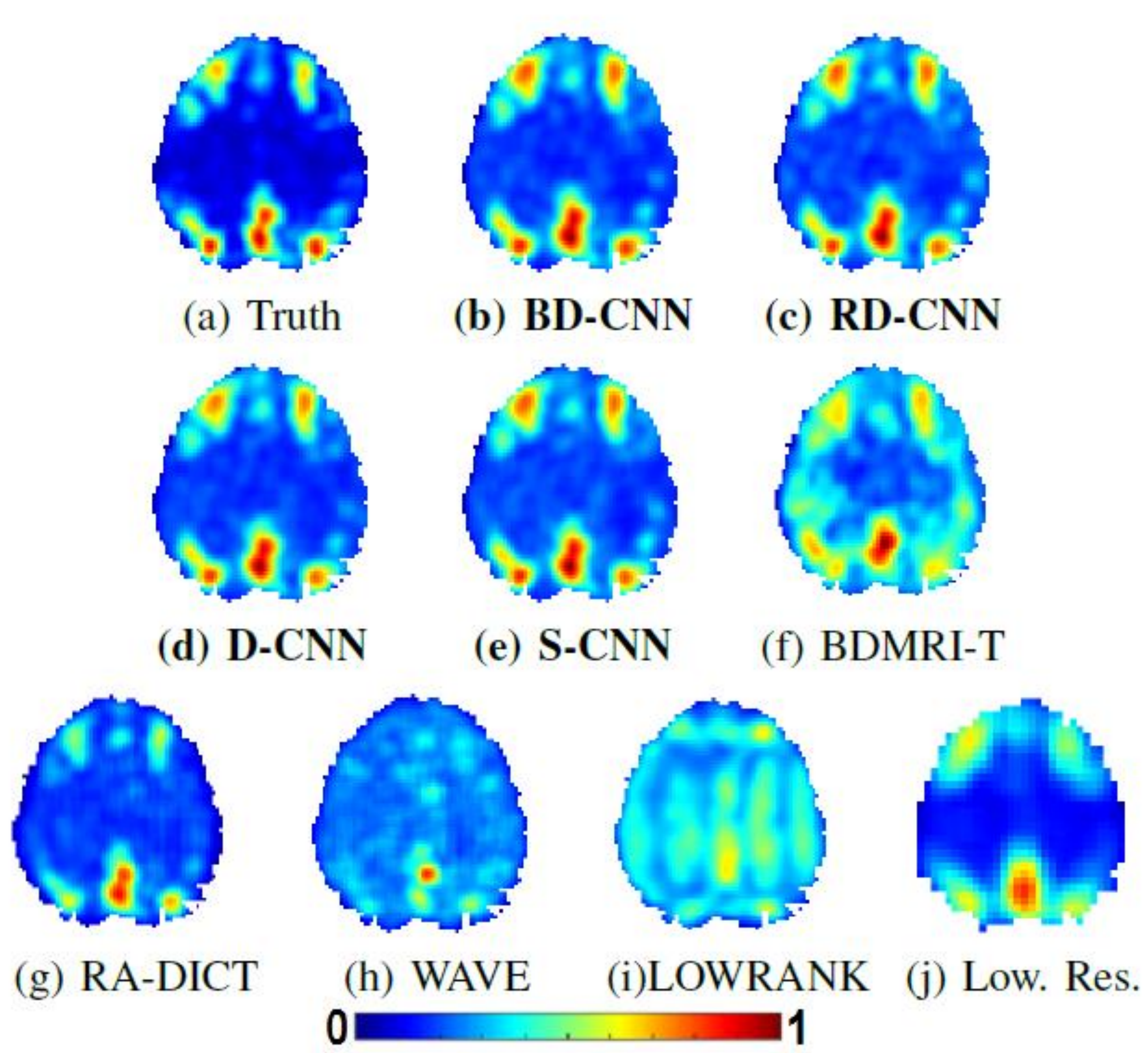
Bayesian Loss:

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

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.



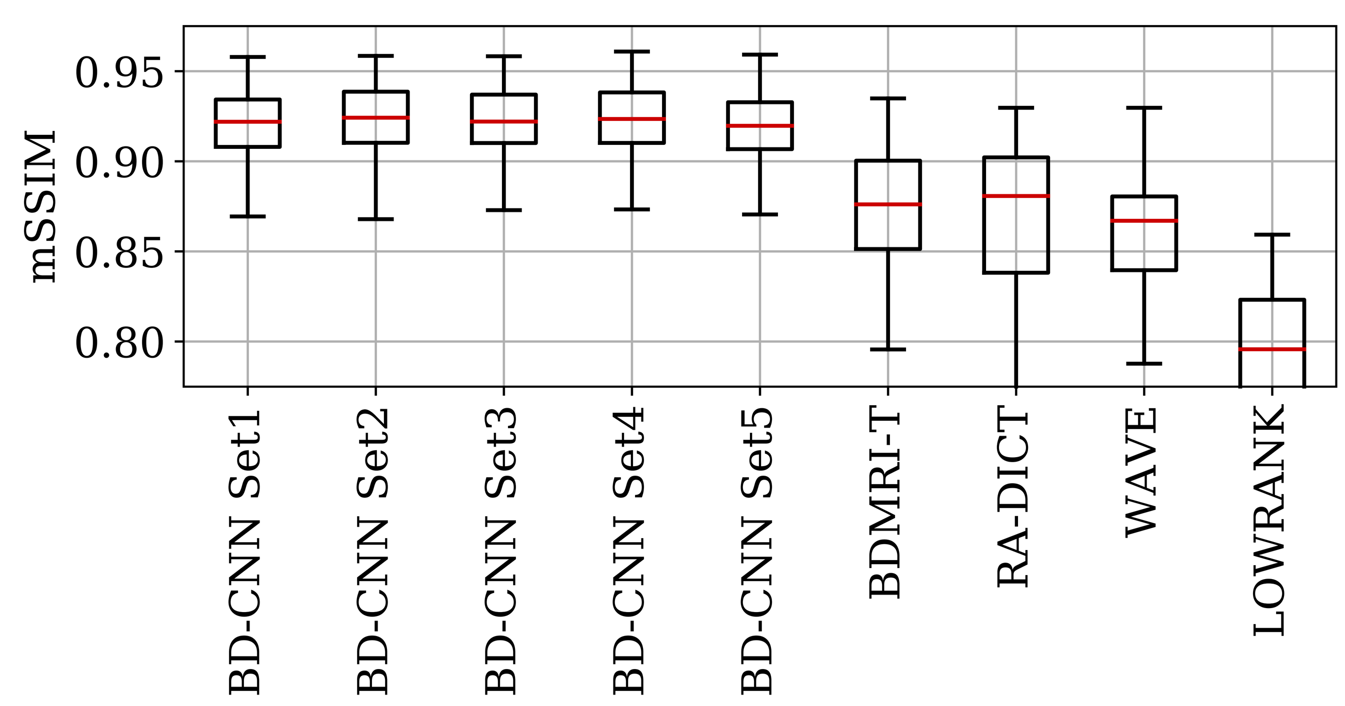


Qualitative Results on Brain R-fMRI: Dorsal Attentive Network (DAN) estimated from (a) original data; from fitted models using (b) **BDCNN**: mSSIM 0.93, (c) **RD-CNN**: mSSIM 0.92, (d) **D-CNN**: mSSIM 0.93, (e) **S-CNN**: mSSIM 0.92, (f) **BDMRI-T**: mSSIM 0:85, (g) **RA-DICT**: mSSIM 0:91, (h) **WAVE**: mSSIM 0:85, (i) **LOWRANK**: mSSIM 0:74; and from (j) 8 × lower spatial resolution of (a): mSSIM 0:82.

Ablation Studies

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 λ

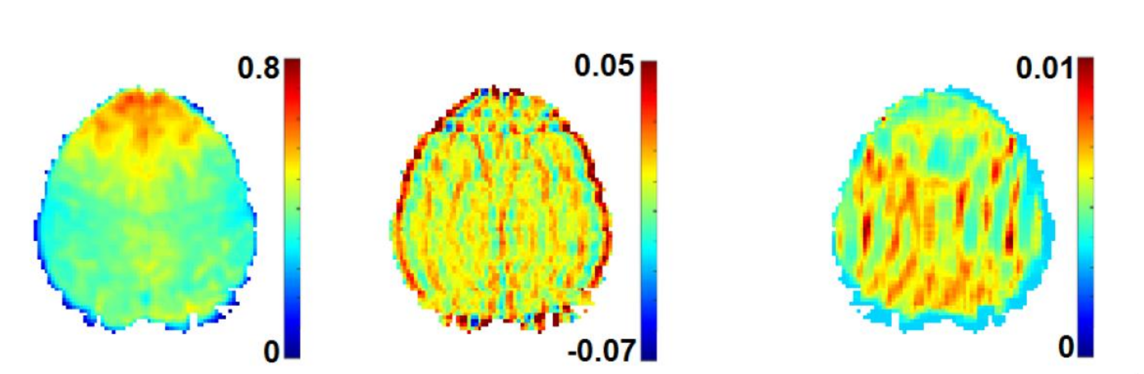
- Trend: Performance deteriorates significantly as $\lambda \to 1^-$.
- Average mSSIM (and standard deviation for all functional networks and evaluation subjects) for $\lambda \in [0,0.75]$ is 0.90 (0.03), and for $\lambda = 1$ is 0.88 (0.03); demonstrates utility of third stage of our architecture.
- 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 (i) **BDCNN**: 0.90 (0.04), (ii) **BDMRI-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 a similar to those in residuals.



(a) Data (b) Residual (c) Uncertainty $\Psi_S(\cdot)$

R-fMRI **(a)** original data, **(b)** residual between original data and zero-filled reconstruction, and **(c)** per-voxel uncertainty map (standard-deviation map $\Phi^S(.)$) in the DAN region.

Infrastructure Facility for Advanced Research and Education in Diagnostics grant by Department of Biotechnology, Government of India (BT/INF/22/SP23026/2017)