k-t FASTER: A New Method for the Acceleration of Resting State FMRI Data Acquisition

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Background: Functional MRI has seen a recent resurgence of interest in fast imaging techniques, to harvest statistical benefit from increased degrees of freedom or to provide novel temporal information. However, fast imaging based on sparsity (e.g., compressed sensing) remains largely unexplored in FMRI because the data is not sparse in any of the conventional transform domains. We propose a more appropriate alternative for FMRI, the related concept of matrix completion[1], which recovers low-rank approximations of under-sampled matrices. This approach is motivated by the well-established observation that FMRI data are well represented at low rank, for example when using principal component analysis for dimensionality reduction prior to using independent component analysis (ICA) to identify resting state networks (RSNs). In effect, this dimensionality reduction represents a transform domain under which the space × time data can be represented with a small number of spatial maps and their associated time-courses[2,3]. We propose to take advantage of these properties to accelerate FMRI acquisition by undersampling in the k-t domain and using matrix recovery to estimate the low-rank k-t matrix approximation. We call this approach k-t FASTER: (FMRI Acceleration in Space-time via Truncation of Effective Rank). k-t FASTER is demonstrated on retrospectively undersampled k-t FMRI data using a novel matrix recovery algorithm, iterative hard thresholding with matrix shrinkage (IHT+MS) to produce high fidelity representations of fMRI RSNs at 4x undersampling. Critically, our results are driven entirely by k-t matrix structure, and constitute a fundamentally different approach from time-independent acceleration techniques that reconstruct volumes based on coil information.

RSN:	#1	#2	#3	#4	#5	# 6	# 7	# 8	# 9	# 10
4x Decimated	0.33	0.34	0.32	0.25	0.29	0.36	0.30	0.22	0.31	0.30
FPCAr (128)	0.34	0.36	0.43	0.45	0.47	0.46	0.41	0.44	0.44	0.50
IHT+MS (128)	0.34	0.38	0.43	**0.46**	0.48	**0.58**	0.47	0.48	0.52	**0.55**
HT+MS (500)	**0.48**	**0.52**	**0.56**	0.33	**0.58**	0.56	**0.55**	**0.55**	**0.58**	0.49

Table 1 – Correlation coefficients between the z-score maps for each dataset and the ground truth data for 10 RSNs.

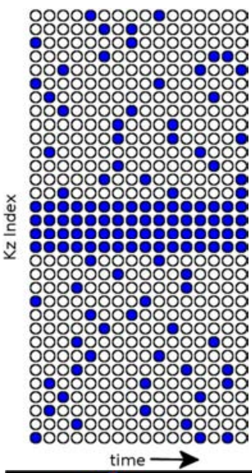

Figure 1 – Example sampling pattern over k_z, with 8/32 k_z planes sampled every time point (filled dots). One full k-space is produced every 7 time points.

Methods: The IHT+MS algorithm combines fixed rank approximation methods (IHT) with nuclear norm minimization methods (MS) to produce a fixed rank k-t matrix approximation (see companion abstract for more details). The IHT+MS algorithm was compared (at reconstruction ranks of 128, 500) with the fixed point continuation approximation method at a fixed rank (FPCAr)[4] of 128. A high temporal and spatial resolution resting state FMRI data set (collected at 3T using a multiband x8 acquisition[5,6], TR = 836 ms, 2x2x2 mm^3) was used for retrospective sampling. The data had spatial and temporal dimensions of 106x106x32 and 512, for a k-t matrix size of 359552x512, where dimensions were limited by algorithm efficiency and do not constitute fundamental reconstruction limits. We simulated 3D-EPI with 4x undersampling of the k_z dimension, where the 4 centre planes were always sampled, and 4 of the remaining 28 planes were randomly sampled every time point (Fig. 1). The original dataset was decimated by selecting every 4th time point to provide a comparison to data from a non-accelerated acquisition with similar imaging parameters. To compare RSNs, MELODIC[7] was run on the original data to produce 100 IC spatial maps. Dual regression was used to estimate equivalent maps for each IC from each reconstructed dataset, and z-scores were null-corrected using mixture modelling[7]. Correlation coefficients were computed between original and reconstructed maps for 10 RSNs, and smoothness values were extracted for all spatial maps by estimating the size of image resolution elements.

Results: Table 1 shows correlation coefficients across the 10 RSNs, indicating that the IHT+MS data produce the highest correlations for all RSNs identified. Fig. 2 shows images from 2 representative RSNs, highlighting the excellent spatial agreement between the original spatial maps and those produced with k-t FASTER using the IHT+MS algorithm. The sagittal images of the fronto-parietal network (Fig. 2, bottom), however, do suggest a loss of spatial fidelity in the undersampled z-direction for the IHT+MS datasets, particularly at rank 500. Average smoothness values indicated that the IHT+MS data at rank 128 and 500 were 29% and 61% smoother than the original maps respectively.

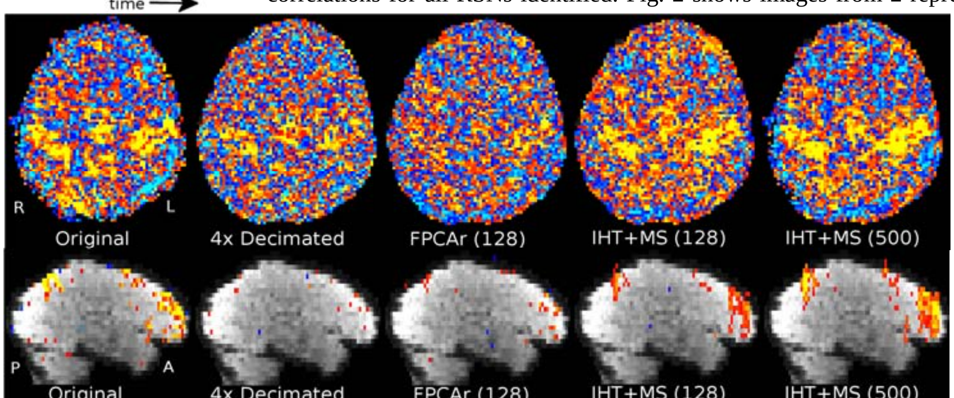

Figure 2 – Comparison of RSN maps. Each image shows unsmoothed z-scores, with red/yellow and blue indicating positive and negative coefficients respectively. Top: Axial, somatomotor cortex (RSN #3, $|z| > 0$). Bottom: Sagittal, right lateralized fronto-parietal network (RSN #9, $|z| > 3$).

Discussion: These results demonstrate the feasibility of k-t FASTER for accelerating the acquisition of FMRI RSN data. Other algorithms previously proposed for matrix recovery in dynamic cardiac MRI[2,3] were not compared here due to poor performance or algorithm efficiency in k-t FMRI data at these ranks and matrix sizes. Future work will aim to demonstrate k-t FASTER in a prospectively undersampled acquisition, as well as to explore algorithmic improvements, including the incorporation of multi-coil information for improved spatial reconstruction fidelity and higher acceleration factors.

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