Acceleration of task-based FMRI using k-t FASTER

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Target Audience Researchers developing methods for accelerating FMRI data acquisition, or interested in applications of highly accelerated FMRI.

Purpose Recently, acceleration of FMRI data acquisition has been demonstrated using different variations of matrix rank-based approaches[1,2]. Here we demonstrate the use of k-t FASTER, initially designed to accelerate resting-state FMRI acquisition[3], to highly accelerate (R=8.25) the measurement of a visual FMRI experiment. k-t FASTER is motivated by the observation that FMRI data is generally treated as a linear combination of a small number of spatio-temporal processes, an assumption that has proven remarkably robust for analyses including task-based GLM, physiological noise removal and independent component analysis. We show that task-FMRI components are also easily recovered using our iterative reconstruction technique. Our approach is combined with a novel hybrid 3D radial-Cartesian undersampling strategy to enable simultaneous use of parallel imaging (R=2), resulting in an acquisition that samples ~4% (1/26) of the k-space required for a fully (Nyquist) sampled radial acquisition.

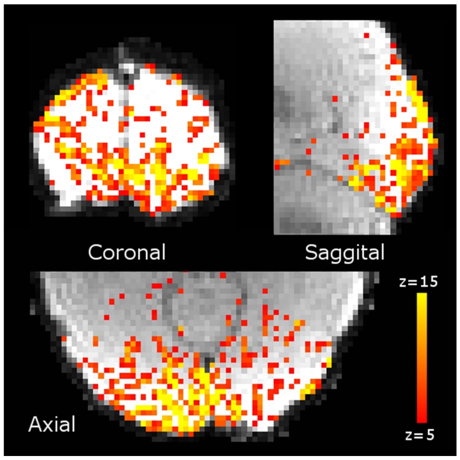

Figure 1 – z-statistic map (|z| > 5) showing robust visual activation in a representative subject.

Methods Simple task-FMRI data was acquired in 3 healthy volunteers at 3 T using a 5 minute, 30 s on/30 s off 8 Hz flickering checkerboard task. A whole-brain 3D hybrid radial-Cartesian sampling strategy was employed[4,5], by rotating a k_{xy}-k_z EPI planar readout about the k_z-axis using a golden angle radial progression, with TR/TE = 50 ms/25 ms. Along the EPI phase encode direction, R=2 parallel imaging was performed, and reconstructed prior to k-t FASTER using GRAPPA[6]. For an output resolution of 2 mm isotropic, full Nyquist-criterion sampling requires $100\times\pi/2 \approx 157$ radial projections (implying a volume TR of 7.85s, which can be seen on Fig 2 as dashed lines), whereas only 12 projections were used to produce each output volume, resulting in a volume TR = 600 ms, and R_{radial} = 13.1, or relative to a 100x100 equivalent Cartesian in-plane acquisition, R=8.25. The data were reconstructed by an inverse Fourier transform in the z-direction, then performing slice-by-slice iterative k-t FASTER reconstruction with a rank constraint of 64. A spatial independent component analysis (ICA) was performed on the 64-dimensional, complex principal component (PCA) subspace estimated by k-t FASTER using FastICA[7] by concatenating real and imaginary parts of the PC spatial maps. Additionally, standard model-based regression z-statistic maps were produced using FEAT (FSL), with no spatial smoothing or residual pre-whitening, and output z-statistics were checked for correct null distributions.

Results Figure 1 shows a 3-axis view of a z-statistic map for a representative subject, highlighting the robust activation observed in visual cortex. Peak z-statistics across all three subjects were 26.0, 21.3, and 24.8, respectively. ICA component results are displayed in Figs 2 and 3. Despite high levels of acceleration, the fidelity of the spatial and temporal components is excellent. Moreover, the use of a task with a pre-specified time-course and well-known activation pattern provides the opportunity to easily probe the components of the low-rank sub-space that k-t FASTER directly estimates. Figure 2 shows the voxel time-series associated with a high z-stat voxel (blue) along with the combination of estimated temporal ICs 1 and 48 (red), which were found to correspond to a slow, linear phase drift and primary BOLD variations respectively. Similarly, in Fig 3, the magnitude spatial map associated with IC 48, shows good correspondence with the z-statistic map of the same slice. These results demonstrate the close link between the spatiotemporal structure that drives the k-t FASTER reconstruction and the information that is used to derive data-driven network analyses like ICA. Nevertheless, the data-driven reconstruction means that there may not be a simple one-to-one correspondence between component features driving the reconstruction and statistics derived from the entire data set. The black arrow indicates a region of non-zero weighting on the IC spatial map, but no correspondingly high z-statistics, which is due to phase cancellation of IC 48 fluctuations from the other complex components.

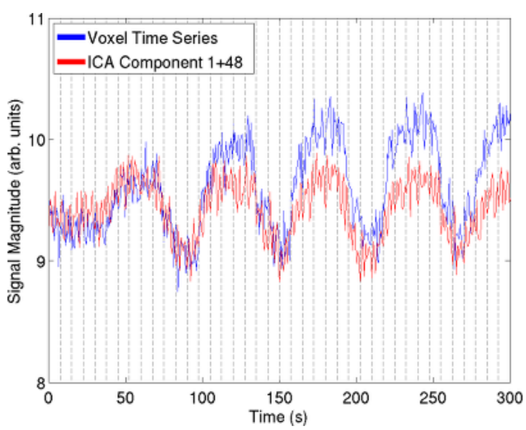

Figure 2 – In black: Time-series (magnitude) associated with a high z-stat voxel. In red: Phased sum of ICs #1 (slow phase drift) and #48 (primary task modulation).

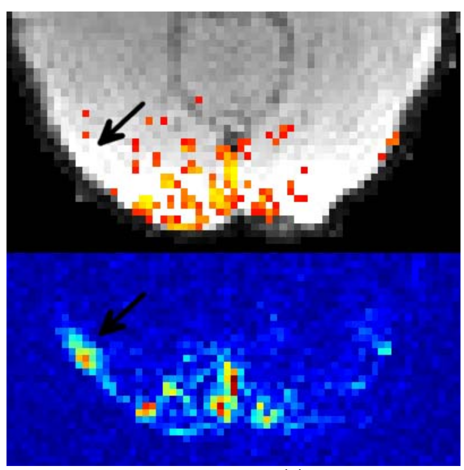

Figure 3 – Top: z-statistic map (|z| > 10) showing regions of significant visual task activation. Bottom: Magnitude spatial map of IC #48.

Discussion The k-t FASTER method is shown here to be capable of capturing simple task-FMRI signals at high acceleration factors, as evidenced by the direct visual task "network" found by searching the directly estimated PCA subspace. The high peak z-statistics for all three subjects suggest a higher sensitivity than traditional acquisition strategies (see also discussions in [8]). Furthermore, k-t FASTER intrinsically reduces noise variance, by restricting the data to a 64-component representation (and rejecting noise), which will boost sensitivity to signals contained in the low-rank reconstructed space.

Conclusion We have demonstrated robust recovery of task-based FMRI data, using k-t FASTER with an acceleration factor of 8.25. Although haemodynamic response characteristics may ultimately limit the utility of ever-faster task-FMRI sampling rates, one application of higher acceleration capabilities in task-FMRI may lie in the facilitation of high and ultra-high resolution imaging in reasonable volume acquisition times, and in reducing artefacts in 3D k-space sampling strategies. Finally, application of ICA to the core k-t FASTER spatial eigenvectors indicates that we can achieve direct reconstruction of meaningful data components (in this case the activation map) without ever carrying out the final full 4-D space×time data reconstruction.

References 1. Lam et al., *ISMRM* 2013 #2620; 2. Nguyen et al., *ISMRM* 2014 #327; 3. Chiew et al., *MRM* 2014; 4. McNab et al., *MRM* 2010; 5. See Graedel et al., *ISMRM* 2015; 6. Griswold et al., *MRM* 2002; 7. Hyvärinen, *IEEE Trans Neural Net* 1999; 8. Feinberg et al., *PLoS ONE* 2010