3D Hybrid Radial-Cartesian Sampling for Improved Resting State FMRI using k-t FASTER

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Target Audience Researchers interested in developing or applying techniques for accelerating resting state FMRI data acquisition.

Purpose Robust investigation of network structure in the human brain using functional magnetic resonance imaging (FMRI) can require a large number of time points, particularly if networks are derived using temporal independence criteria[1]. We previously introduced a new method for accelerating FMRI data acquisition called k-t FASTER[2], which exploits the fact that analysis models have shown that most of the salient network information in FMRI data lies in a low dimensionality (low rank) subspace, and that low rank data have reduced degrees of freedom that permit undersampled recovery[3]. Our previous work focused on a 3D EPI sampling strategy, which resulted in limited acceleration factors due to central k-space sampling requirements, and more coherent artefacts. Here we demonstrate our rank constrained k-t FASTER approach with 3D hybrid golden angle radial-Cartesian k-space sampling[4,5], which densely samples central k-space regions, facilitates flexible volume sampling rates (and undersampling factors), and reduces artefact coherence. Recovery of resting state network (RSN) information across varying acceleration factors is explored, with volume TRs ranging from 3 s to 0.4 s in the same data.

Methods Figure 1 shows a schematic of the k-space sampling trajectory consisting of radial "blades," which are EPI readouts (phase encode along k_z), rotated about the z-axis according to an angular increment defined by the golden ratio (111.25º). This increment scheme is known to produce nearly uniform k-space sampling for arbitrary contiguous subsets of blades[6], which allows the volume TR of the acquisition (dictated by the number of blades contributing to a single time point) to be chosen *post hoc*, based on maximum tolerable undersampling factors. Data were acquired in 2 healthy volunteers at 3 T, using a TR/TE = 50/25 ms, and a parallel imaging acceleration factor of 2 along the EPI phase encode direction, which was reconstructed using GRAPPA prior to k-t FASTER. Sampling parameters were chosen for an output whole-brain resolution of 2 mm isotropic, which would require about 157 ($100\times\pi/2$) blades per time point to radially sample according to Nyquist criteria. A total of 6000 blades were acquired over a 5 minute duration, and reconstructed at R=1.67x (60 blades/time point), R=2.5x (40), R=3.33x (30), R=5.0x (20), R=6.67x (15), R=8.33x (12), R=10x (10), and R=12.5x (8) in one subject, and at R=1.67, 2.5, 3.33, 6.67, 10 and 12.5x in the second subject, where acceleration factors are reported relative to the efficiency of an equivalent Cartesian acquisition. Reconstructions were performed slice by slice after inverse Fourier transform along the z-direction, at rank 64 in all cases by solving the optimisation problem:

$$\min_X \begin{matrix} \|Y - nuFFT(SX)\|_2 \\ s.t.\ \text{rank}(X) = 64 \end{matrix},$$

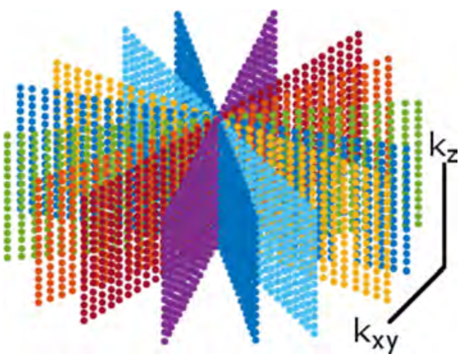

Figure 1 – Schematic diagram of the hybrid radial-Cartesian k-space sampling strategy. Each radial projection is an entire EPI readout along k_z, and the projections are rotated by 111.25º every TR.

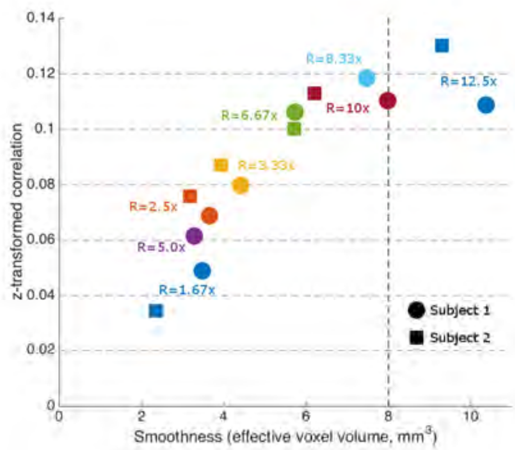

Figure 2 – Scatter plot of z-transformed correlations of the dual regression output maps with model network maps, and smoothness estimates of the z-statistic maps, across various reconstructed acceleration factors. Marker size encompasses standard errors.

where Y are the multi-coil k-space measurements, S is a sensitivity matrix, and X is the estimated data. A non-linear, multi-coil iterative hard thresholding and matrix shrinkage algorithm was used to solve the optimisation[7], and the non-uniform FFT ($nuFFT$) operator was provided by the NUFFT toolbox[8]. Following reconstruction, the data were analysed for resting state network expression by performing a dual regression against a set of 64 model regressors derived from a separate, large group average dataset[9].

Results Figure 2 shows the results of the reconstructions at varying acceleration factors, assessed by z-transformed correlation of dual regression output maps with the model networks, and smoothness of the z-stat maps (in resels), averaged across all 64 networks studied. As expected, RSN fidelity increases with increasing acceleration (and corresponding increase in the temporal degrees of freedom), until it becomes too high for the rank-constrained reconstruction to produce reliable data. As a result, RSN correlations can decrease (subject 1), and data begin to show degradation of spatial resolution (both subjects), which can be seen in the R=12.5x data when the smoothness measure exceeds the prescribed voxel volume of 8 mm[3]. Figure 3 shows z-statistic a RSN map from the R=3.33, 8.33 and 12.5x datasets of the first subject, selected to demonstrate the general trend.

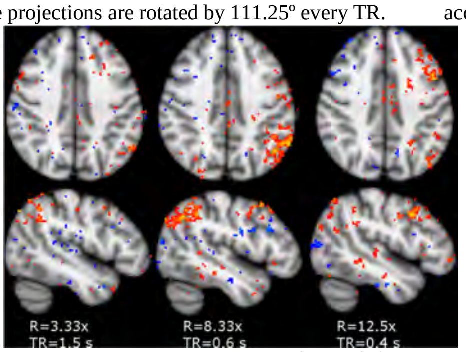

Figure 3 – z-statistic maps ($|z| > 2.3$) for a left fronto-parietal network, across three different acceleration factors.

Discussion The hybrid-radial acquisition scheme allows reconstruction to be optimised for maximum data efficiency, by permitting multiple *post hoc* choices for temporal bin widths while maintaining uniform k-space coverage. One drawback of this sampling approach is that the densely sampled centre of k-space combined over multiple shots can cause phase cancellation and artificial signal dropout or variance. Increasing the acceleration factor reduces this effect, but may introduce additional artefacts due to high degrees of radial undersampling. The balance of temporal degrees of freedom with reconstruction quality leads to an optimal acceleration factor, found here to be around R=8.33-10x, corresponding to a volume TR=0.5-0.6 s. Shot-by-shot phase correction approaches may also significantly improve the quality of multi-shot data[5].

References 1. Smith et al., *PNAS* 2012; 2. Chiew et al., *MRM* 2014; 3. Candes et al., *IEEE Trans Info Theory* 2010; 4. McNab et al., *MRM* 2010; 5. See Graedel et al., *ISMRM* 2015; 6. Winkelmann et al., *IEEE TMI* 2007; 7. Chiew et al., *ISMRM* 2014; 8. Fessler et al., *IEEE Trans Sig Proc* 2003; 9. Van Essen et al., *NeuroImage* 2013;