Joint multi-coil and low-rank constraints for accelerating FMRI data acquisition using k-t FASTER

Mark Chiew[1], Stephen M Smith[1], Thomas Blumensath[2], and Karla L Miller[1]
[1]FMRIB Centre, University of Oxford, Oxford, Oxfordshire, United Kingdom, [2]IVSR, University of Southampton, Southampton, Hampshire, United Kingdom

Purpose Increasing temporal resolution in FMRI has been largely dependent on time-independent methods based on multi-coil information. Although strategies based on exploiting limited k-t support [1] or k-t sparsity [2] have been proposed, they have not seen wide adoption. Recently however, a novel method for accelerating FMRI data using rank-constrained reconstruction, called k-t FASTER [3], has been demonstrated to successfully extract resting state networks (RSNs) without relying on coil information. This approach exploits well-established low-rank structure in resting FMRI data, which permits the large dimensionality reductions common to RSN analysis pipelines. In k-t FASTER, spatio-temporal bases are blindly estimated, without requiring *a priori* knowledge of k-t support or sparsifying transforms. In this abstract, we enhance k-t FASTER by incorporating coil-based data consistency constraints to take advantage of the extra information provided by multiple receive coils. This synergistic approach to low-rank matrix reconstruction produces datasets with lower reconstruction errors and can facilitate acquisition at higher acceleration factors than can be achieved with rank- or coil-based accelerations alone.

Methods Originally, the iterative hard thresholding with matrix shrinkage algorithm (IHT+MS) [4], which drives the k-t FASTER reconstruction, was designed to reconstruct the k-t matrix without explicit knowledge of parallel coil acquisitions. Our proposed multi-coil enhancement projects the estimated k-t matrix into a multi-coil k-t space for error calculation, and transforms the error term back into a composite k-t space using the SNR-optimal coil combination method [5] for weighted addition to the current estimate. Rank truncation and matrix shrinkage proceed normally on the k-t matrix estimate. The algorithm can be summarised as: $x^{n+1} = S\left(x^n + \mu\Psi^-(y - \Phi\Psi^+x^n)\right)$,

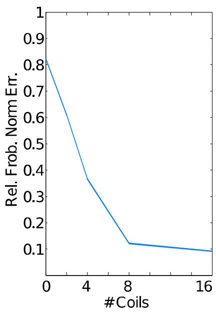

Figure 1 – Relative Frob. norm errors.

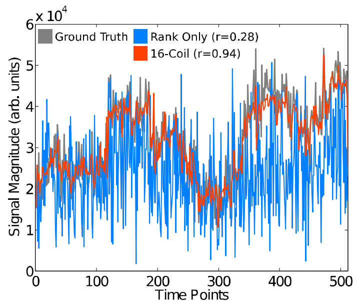

Figure 2 – Representative magnitude k-space time series comparisons.

where Ψ^+ and Ψ^- represent the transforms for the forward projection onto multi-coil space and the reverse projection into the composite space respectively (requiring explicit knowledge of coil sensitivities), x^n is the n^{th} matrix estimate, S is the rank truncation and shrinkage operator, μ is a step size, y is the measured data, and Φ is a sampling operator. This approach takes advantage of the fact that the number of independent measurements increases in proportion to the number of coils, whereas the number of unknowns remains unchanged because a single "true" (i.e. non-coil weighted) k-t matrix is estimated. This method was tested using a simulated 16-channel coil with complex Gaussian sensitivity profiles and retrospective 8-fold random under-sampling of an FMRI dataset with a 53x53x32 spatial matrix, and 512 time points. Zero-mean complex Gaussian noise was added to each coil measurement with 5% standard deviation, and no noise covariance between coils. Multi-coil reconstruction using 2, 4, 8 and 16 coil subsets were compared, as well as 16 averages of the original k-t FASTER method the same additive noise, but absent any coil weighting (i.e., using only rank constraints). All methods used a rank cutoff of 128.

Results The results illustrate the simulated case where rank-only reconstruction performs poorly, and multi-coil k-t FASTER greatly improves reconstruction metrics. Figure 1 shows the decrease in relative Frobenius norm error with various coil subsets (rank-only = 0 coils), achieving <10% error with 16 coils. Figures 2 and 3 show representative magnitude time-series and image error respectively, highlighting the fidelity of the 16-coil reconstruction. Figure 4 shows a z-statistic map from a dual regression analysis against a set of canonical RSN maps, where the 16-coil reconstruction map shows good agreement with ground truth, in contrast to the rank-only data.

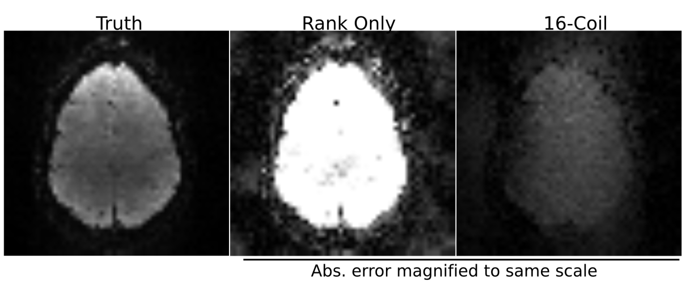

Figure 3 – Example magnitude image errors from the rank-only and 16-coil reconstructions. The reconstructed images are windowed identically.

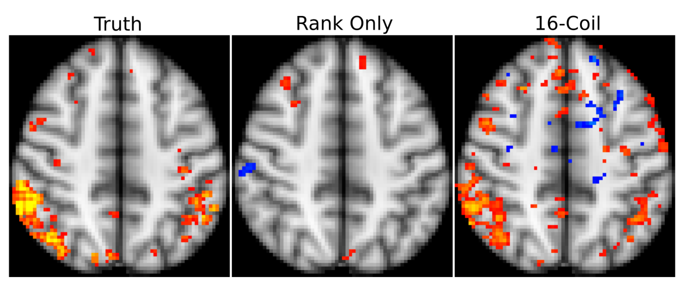

Figure 4 – Z-statistic maps thresholded at |z|>2.6 for the right dorsal stream RSN. The 16-coil recon shows good agreement with truth.

Discussion These results show power of the multi-coil reconstruction in a regime where the 8x under-sampling factor and target rank of 128 do not permit robust recovery using rank constraints alone, and where coil-only parallel imaging would also not be feasible. Other reported approaches to multi-coil low-rank reconstruction include a tensor-expansion method [6], and integrated SENSE-combination method [7], which is similar to the approach presented here. The multi-coil k-t FASTER method, however, is a simple implementation of this concept, using a straightforward greedy algorithm that has already demonstrated to have potential for accelerating FMRI data acquisitions [3]. This approach is expected to be particularly powerful for identification of resting-state networks, where existing k-t accelerations are insufficient for capturing the broad-band temporal information that is not well described by strict low-rank models.

References 1. Madore et al., MRM 1999; 42(5): 813-28, 2. Jung et al., Phys Med Biol 2007; 52(11): 3201-26, 3. Chiew et al., ISMRM 2013 #3274, 4. Chiew et al., ISMRM 2013 #3792, 5. Roemer et al., MRM 1990; 16(2):192-225 6. Trzasko et al., ISMRM 2013 #0603, 7. Otazo et al., ISMRM Sedona Workshop 2013