A Distributed Compressive Sensing Strategy for Non-Cartesian MRI: Applications to SWIRLS CE-MRA

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Introduction: SWIRLS is a centrically-ordered 3D spherical non-Cartesian trajectory that has recently demonstrated promising results for time-constrained applications such as single phase contrast-enhanced magnetic resonance angiography (CE-MRA) [1]. As the point spread function (PSF) of the SWIRLS sampling operator is highly incoherent, it is also well-suited for use within a compressive sensing (CS) [2] framework for accelerated acquisition. In this work, we describe a novel and efficient sparse reconstruction strategy for undersampled multi-channel 3D non-Cartesian MRI, and apply this technique to accelerate SWIRLS CE-MRA acquisitions. It is demonstrated that the proposed approach improves image quality compared to a standard gridding reconstruction strategy currently employed for SWIRLS.

Methods: Suppose we model our signal acquisition as $G=AF$, where F is an N^3xC matrix corresponding to (a discrete approximation of) the multi-channel signal of interest, and A is a $N^3 \rightarrow K$ ($K<N^3$) discrete-time Fourier transform (DTFT). Since the reconstruction of F from G is underdetermined, auxiliary constraints are needed to identify a solution. As demonstrated in [3-6], in multi-coil settings it is advantageous to exploit joint signal sparsity across the coil dimension. In [7,8], redundant sparsifying transforms were observed to facilitate superior reconstructions relative to global orthonormal transforms. Here, we synergistically combine these strategies and consider the following equality-constrained reconstruction model:

$$\hat{U} = \arg\min_{U} \sum_{b\in\Omega} \left\| \Psi R_b U \right\|_{1,2} \quad s.t. \quad AU = G \tag{1}$$

where $\|\cdot\|_{1,2}$ is the ℓ_1-ℓ_2 matrix norm, Ψ is the orthonormal 3D discrete cosine transform (DCT) dictionary [9], R_b is a B^3xN^3 3D block extraction operator, and the block set Ω is such that $\Sigma R_b^* R_b = \alpha I$ ($\alpha>0$). In Cartesian applications, equality-constrained sparse reconstruction problems are often solved via projections-onto-convex-sets (POCS), which alternates between explicitly enforcing the Fourier-domain equality constraint and image/transform domain thresholding (e.g., [6]). More explicitly, this iteration is defined as: $U_0=0$; $U_{t+1}=P_2(P_1(U_t))$. For non-Cartesian applications, A is not invertible and so this equality constraint cannot be explicitly enforced. However, it can be implicitly enforced via the following affine projection:

$$P_1(U) = \left[I - A^*\left(AA^*\right)^{-1} A \right] U + A^*\left(AA^*\right)^{-1} G = U - A^*\left(AA^*\right)^{-1}\left(AU - G\right) \tag{2}$$

As inversion of the crosstalk matrix is computationally demanding, we approximate (2) as $P_1(U)\approx U-A^*D(AU-G)$, where the diagonal matrix D is estimated via positive semi-definite constrained least squares regression [10]. Note that this projection is semantically similar to the update step of gradient descent based methods (e.g., [11,12]). Minimization of the objective functional in (1) can be (approximately) realized via the following convex projection:

$$P_2(U) = \alpha^{-1} \sum_{b\in\Omega} R_b^* \Psi^* S_\lambda\left(\Psi R_b U\right) \tag{3}$$

where the joint soft-thresholding operator (with threshold λ) is defined as

$$\left[S_\lambda(Y)\right]_{x,c} = \frac{Y_{x,c}}{\left\|Y_{x,:}\right\|_2}\left(\left\|Y_{x,:}\right\|_2 - \lambda\right)_+ \tag{4}$$

In this work, POCS minimization of (1) was implemented in C++ using the FFTW, OpenMP, and Eigen software libraries. The SWIRLS operator, A, was realized using a 1.25x oversampled, W=5, Kaiser-Bessel non-uniform fast Fourier transform (NUFFT) [13,14]. To facilitate collision-free parallelization of (3), Ω comprises uniformly distributed blocks adhering to periodic boundary conditions, such that it can be readily decomposed into subsets of disjoint blocks for parallel processing.

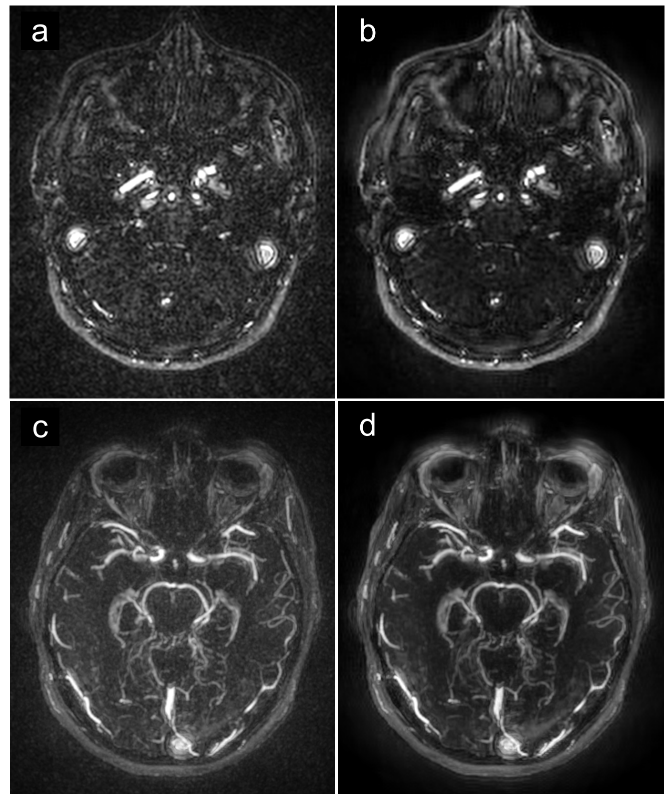

FIG 1: Example reconstructions of a ~3.35x undersampled single-phase SWIRLS CE-MRA acquisition. Both axial cross-sections (a-b) and 1cm targeted MIPs (c-d) are shown. (a,c) correspond to standard gridding reconstruction, whereas (b,d) correspond to the proposed compressive sensing reconstruction. Notice that the noise and aliasing artifact present throughout the gridding reconstructions are largely absent in the compressive sensing reconstruction images, which results in improved vessel conspicuity. All images are windowed and leveled identically. See text for acquisition and reconstruction details.

Results: Figure 1 compares standard gridding [1] with the proposed sparsity-driven reconstruction for a volunteer that was scanned at 3T (GE, DVMR 20.1IB, Milwaukee, WI) under an IRB-approved protocol using an accelerated single-phase SWIRLS acquisition (FOV=24cm, TR=7.4ms, TE=3.4ms, BW=±62.5kHz, FA=35°, 8047 shots, 512 samples/shot, 8-channel receive-only head coil). The acquisition time was approximately 1 minute. A 2 mL test bolus was used in a timing fluoroscopy, and a 12 mL bolus of gadobenate dimeglumine contrast (Multihance, Bracco Diagnostics, Princeton, NJ) was injected into the right antecubital vein at 3 mL/s, followed by a power-injected 50 mL saline flush. Both reconstructions were for N=240. For the proposed reconstruction, B=8 was used, and Ω corresponded to the set of all block spaced by 4 voxels in each dimension (half-block overlap). λ was manually selected. On a dual 6-core (Intel x5670, 2.93 GHz, 12 MB cache) machine with 24 GB DDR3 1333 MHz memory, each iteration of the POCS reconstruction required about 24 s of computation. The result in Figure 1 was obtained after 25 iterations, in about 10 minutes. For reference, standard gridding requires only ~12 s of computation. In the both the axial slice and targeted maximum intensity projection (MIP) images, notice that the proposed reconstructions exhibit reduced noise and aliasing artifact than the standard gridding reconstructions, leading to improved anatomical detail and vessel conspicuity.

Summary: In this work, we have proposed a novel sparsity-driven reconstruction strategy for multi-channel 3D non-Cartesian acquisitions, and demonstrated its performance benefits with undersampled, single-phase SWIRLS CE-MRA. The improved image quality and manageable reconstruction time may also make time-resolved SWIRLS acquisitions more feasible. Future directions include the incorporation of off-resonance and eddy current correction, utilization of learned dictionaries in lieu of the DCT [15], and employment for other 3D non-Cartesian applications and/or acquisition strategies.

References: [1] Y. Shu et al., ISMRM 2011:2656; [2] M. Lustig et al., MRM 58:1182-95, 2007; [3] D. Liang et al., ISMRM 2009:377; [4] R. Otazo and D. Sodickson, ISMRM 2009:378; [5] Lustig et al., ISMRM 2009:379; [6] M. Akcakaya et al., JMRI 33:1248-55, 2011; [7] C. Baker et al., ISMRM 2009:4583; [8] C. Baker et al., ISBI 2011:1602-05; [9] O. Guleryuz, IEEE TIP 16:3020-34, 2007; [10] submitted to ISMRM 2012; [11] N. Seiberlich et al., ISMRM 2010:4873; [12] G. Lee et al., ISMRM 2011:360; [13] J. Fessler and B. Sutton, IEEE TSP 51:560-64, 2003; [14] P. Beatty et al., IEEE TMI 24:799-808, 2005; [15] S. Ravishankar and Y. Bressler, ISMRM 2011:2830