Nonconvex Compressive Sensing with Parallel Imaging for Highly Accelerated 4D CE-MRA

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Overview: CAPR [1,2] is a state-of-the-art SENSE-type [3] parallel acquisition paradigm for Cartesian 3D time-resolved (4D) contrast-enhanced MR angiography (CE-MRA) that combines high-resolution calibration scans, custom coil arrays, and a flexible undersampled 3DFT sequence to generate diagnostic-quality images at acceleration factors of 10-40x. CAPR images are typically reconstructed online using Tikhonov and partial Fourier methods [1,4] to permit immediate clinical assessment; however, when operating at extreme acceleration rates, such reconstructions can exhibit significant noise amplification and Gibbs artifacts. In this work, an offline reconstruction framework for both view-shared and non-view-shared CAPR time-series acquisitions based on nonconvex Compressive Sensing (NCCS) [5,6] is proposed and demonstrated to both suppress noise amplification and improve vessel conspicuity.

Methods: Immediately following contrast injection but prior to bolus arrival in the vasculature of interest, several time frames are collected to serve as subtraction references. Following this initialization period, subsequently acquired k-space data is background subtracted and then entered into a storage buffer. If a view-shared reconstruction is desired, a subset of the k-space indices not measured at the time point of interest is populated using previous acquired data stored in the buffer, and this composite data set is passed into the reconstruction engine. Letting $g_c(t)$ denote the measured set of k-space values associated with the c^{th} coil at time t, and noting that CE-MRA images are compressible under spatial gradient operators [7], a single image volume at time t is estimated as

$$u(t) = \arg\min_{u} \alpha \sum_{n\in\eta} P(D_n u) + \sum_{c=0}^{C-1} \left\| \Phi \Gamma_c u - g_c(t) \right\|_2^2 \qquad (1)$$

where D_n is a finite difference operator (zero Neumann boundary conditions), η is the set of six cardinal offsets (forward and backward in xyz) over which finite differences are computed, Φ is a partial 3DFT operator, Γ_c is the c^{th} coil sensitivity profile, $P()$ is a nonconvex prior functional (e.g. Laplace error functional [5]), and α is a regularization parameter. For $t\geq 0$, $u(t-1)$ is employed as a warm-start estimate of $u(t)$; $u(t<0)=0$ is assumed. (1) was minimized using the inexact quasi-Newton solver described in [6], with the number of outer Newton and internal CG iterations fixed (typically 5 and 15-25). As there is relatively little change in contrast intensity and distribution between successive time frames, the solution from one time frame will generally be very close to that of the next frame, facilitating rapid convergence in the Newton-type framework and helping to avoid many of the spurious local minima that can arise during nonconvex optimization. In addition, Chartrand's ε-continuation technique [8] is employed for improved convergence and robustness. The reconstruction system is currently implemented in C++ using the FFTW and MPI libraries and executed on an 8-node cluster system, where each node holds two 3.4 GHz Xeon processors and 16GB memory [9]. On this system, offline reconstruction of a single 400x312x132 volume from a 12-coil data set requires roughly 6 minutes of computation, or about 3 hours to reconstruct an entire time series of 35 volumes.

Results and Discussion: When considering the acquisition and reconstruction of an N_xxN_yxN_z volume from an array of C coil data sets each of which contains M phase encode views, we define the acceleration factor (AF) and undersampling factor (USF) as $AF=(N_yN_z)/M$ and USF=100x(1-min{C/AF,1}). Note that $USF>0$ only if $AF>C$, otherwise it is zero due to the fact that the reconstruction problem is either exactly or overdetermined (albeit potentially rank deficient). Fig. 1 compares the results of a typical acquisition of the foot of a patient following view-shared partial Fourier and NCCS reconstructions. In this study, 27 volumes (N_xxN_yxN_z=400x320x220, 0.8mm x 0.8mm x 1mm) were acquired with C=8 coils with temporal resolution of 6.7s and a temporal footprint of 27s; AF=19.7, USF = 59.3. Fig. 2 compares the results of a typical acquisition of the calves of a volunteer following non-view-shared partial Fourier and NCCS reconstructions. In this study, 35 volumes (N_xxN_yxN_z=400x312x132, 1mm^3) were acquired with C=12 coils with temporal resolution of 4.3s; AF=61.1, USF = 80.4. Observe in both examples that the NCCS reconstruction is able to resolve secondary branching vessels that are otherwise lost in noise or geometrically distorted in the partial Fourier reconstruction. Similar behavior was consistently observed across over a dozen different studies of the calves, feet, and head, both with and without view-sharing, and all with acceleration factors exceeding the number of coils.

References: [1] Haider et al., MRM:60(3), 2008; [2] Haider et al., ISMRM:2649, 2009; [3] Pruessmann et al., MRM:46(4), 2001; [4] King and Angelos, ISMRM:1771, 2000; [5] Trzasko and Manduca, IEEE TMI:28(1), 2009; [6] Trzasko et al., ISBI, MO1.R4.4,2009; [7] Lustig et al., MRM:58(6), 2007; [8] Chartrand and Yin, ICASSP:3869, 2009; [9] Borisch et al., ISMRM:1492, 2008.

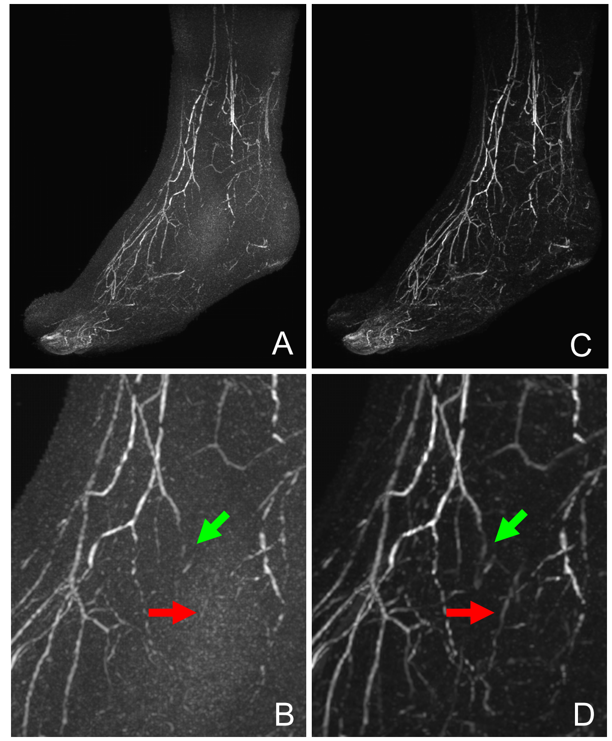

Fig. 1: Comparison of view-shared partial Fourier (a,b) versus NCCS (c,d) reconstructions of early filling in the foot.

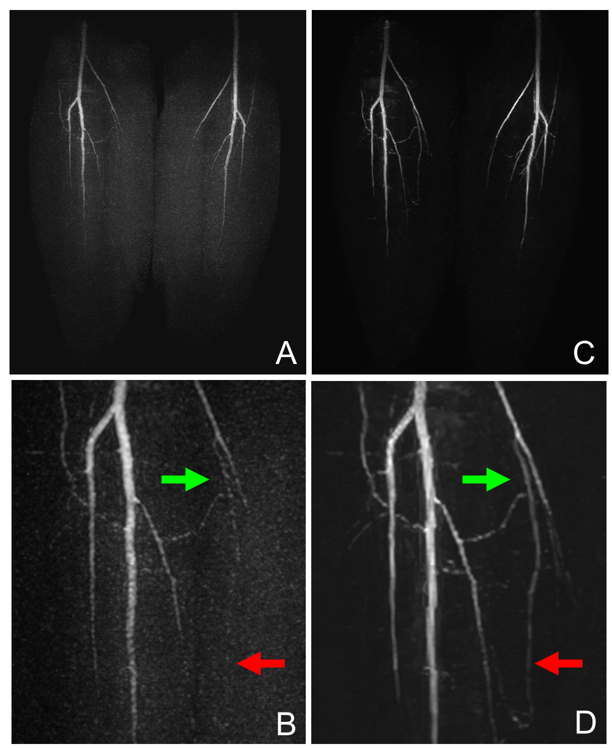

Fig. 2: Comparison of non-view-shared partial Fourier (a,b) versus NCCS (c,d) reconstructions of the early filling in the calf.