

Application-Specific Compressed Sensing for Improved Spatial and Temporal Resolution of Intracranial CE MRA

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Introduction: Depiction of rapid contrast bolus propagation dynamics in intracranial time-resolved contrast-enhanced (CE) MR angiography (MRA) typically requires significant data undersampling per time frame. Radial data acquisition in combination with view sharing [1], parallel MRI [2], and compressed sensing (CS) [3] showed a viable potential to produce useful CE MRA image series. However, at high accelerations many existing techniques fail to fully restore spatial frequency information in highly undersampled areas due to inherent limits on achievable acceleration factors. Because in radial imaging undersampling grows with k -space radius, the incomplete restoration affects outer k -space areas most resulting in spatial resolution loss even in the absence of noticeable undersampling (streaking) artifacts. In this work, we propose a novel data-driven CS-type reconstruction which demonstrates higher acceleration capabilities than standard CS techniques and improves spatial resolution and visualization of fine vessel structures.

Theory: The problem of reconstructing image series \mathbf{f} is a system of linear equations $\mathbf{Ef} = \bar{\mathbf{b}}$, where \mathbf{E} is the encoding matrix, and $\bar{\mathbf{b}}$ is the vector of measured k -space data for all time frames. If k -space data is incomplete, the above equation has infinitely many solutions. To isolate a single solution, prior information about the image series is invoked to constrain the solution. Standard CS approaches exploit sparsity of the image series after application of general transforms, such as wavelets or spatial/temporal gradients, implemented through minimization of a cost function: $\min_{\mathbf{f}} (\|\mathbf{Ef} - \bar{\mathbf{b}}\|_2 + \lambda \|\mathbf{Df}\|_1)$ Eq. [1], whose size is measured by ℓ_p norms ($\|\mathbf{x}\|_p^p = \sum |x_n|^p$). Here, we propose a new application-specific approach to transform design, which takes into account physical properties of contrast dynamics. We tailor our transform design to CE MRA by exploiting the fact that first-pass contrast bolus propagation and recirculation can be modeled by a linear combination of two gamma-variate curves [4]. Our approach, whose pipeline is given in Fig. 1, is initialized by low-resolution image series from fully-sampled k -space center (e.g. SENSE-reconstructed images [2]). Parameters of the contrast propagation model are estimated from the initial series by a pixel-wise non-linear model fit to the image series (Step 1). The parameters of the fit are then used to construct a sparsifying model-consistency transform as $\mathbf{D} = \mathbf{G}\mathbf{G}^*$ (Step 2). Here, \mathbf{G}^* is the pixel-wise model fitting operator, \mathbf{G} synthesizes a model waveform from model parameters, and \mathbf{I} is the identity operator. The next image series estimate is obtained by solving Eq. [1] (Step 3), with the procedure repeated iteratively until convergence. The proposed CS formulation with model-based penalty term (MBCS) enforces general adherence to the model, while the use of robust ℓ_1 norm preserves altered temporal dynamics (e.g., due to contrast extravasation effects).

Methods: A digital phantom (128 x 128 x 32) simulating both normal and abnormal contrast dynamics was used to generate single coil radial data with acceleration factor $R=6$. Following informed consent, in-vivo CE MRA data were acquired in an aneurysms patient using hybrid radial/Cartesian sampling on a 3.0 T clinical scanner (Discovery™ MR750, GE Healthcare, Waukesha, WI) with 8-channel head coil (TE/TR=1.5/4 ms, FA=25°, BW=125 kHz, 20 slices, voxel size 0.86x0.86x2 mm³) and reconstructed from 15 projections/slice per 1.2 s time frame ($R=27$) using iterative SENSE, standard CS with temporal gradients [3], and the proposed MBCS. Arterial phase frame (AF) was reconstructed by PILS [6] combining projections from 8 frames ($R=3.3$), which were reconstructed separately by MBCS and averaged to get AF.

Results: Images in Fig. 2 show that although low-resolution model used for MBCS transform describes only normal contrast dynamics (ROI #1,2) but not the deviating curve (ROI #3), MBCS yields accurate restoration of the dynamics and spatial resolution in all structures. Images in Fig. 3a illustrate that improved spatial resolution of MBCS reconstruction of aneurysm patient data for each slice translates into better visualization and delineation of small vessels in the MIP images. Spatial resolution gain of MBCS over SENSE and standard CS is further confirmed by examining pairwise image differences (Fig. 3b), which show that MBCS restores most higher spatial frequency information compared to SENSE and standard CS. MBCS restores the arterial frame with resolution comparable to gridding-based PILS but with much improved SNR (Fig. 3c). MBCS preserves (Fig. 3d) temporal dynamics of SENSE in large (not-affected by resolution loss) structure (aneurysm, red arrow in Fig. 3c), and improves (Fig. 3e) the waveform in the smaller (resolution-affected) structure (aneurysm feeding artery, green arrow in Fig. 3c).

Discussion and Conclusions: The proposed data-driven, model-based CS reconstruction showed ability to improve spatial resolution and SNR in highly accelerated CE MRA. Moreover, MBCS was able to preserve temporal dynamics of contrast propagation in both normal and pathological vessels. The demonstrated advantages are due to the novel application-specific transform that exploits physical properties of contrast dynamics. This makes our approach more efficient than standard CS methods relying on transforms inherited from general image processing field. Our method may also improve spatial and temporal fidelity in other application based on first pass bolus tracking such as dynamic susceptibility perfusion weighted MRI.

REFERENCES: [1] Barger AV et al., MRM 2002; 48:297. [2] Pruessmann KP et al., MRM 2001;41:638. [3] Velikina JV et al. Proc ISMRM 2010:4865. [4] Davenport R, NUCL Med 1984;24:9454. [5] Griswold MA et al., MRM 2000;44:602.

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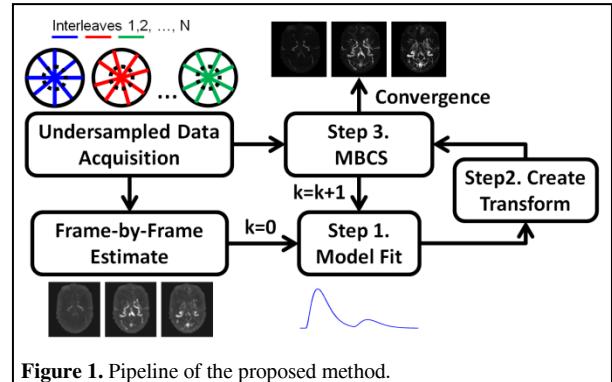


Figure 1. Pipeline of the proposed method.

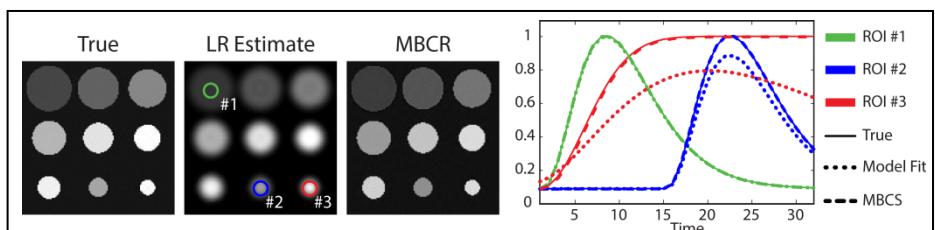


Figure 2. Robustness of MBCS to signals unexplained by the model used for MBCS transform design from initial low-resolution estimates.

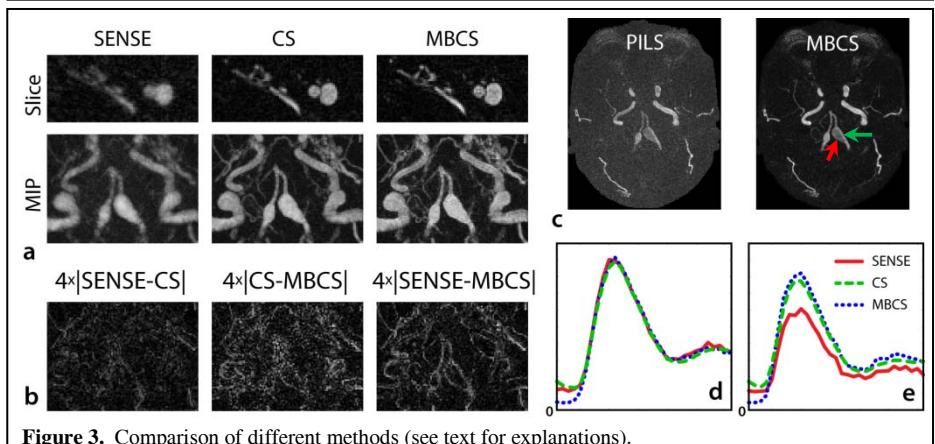


Figure 3. Comparison of different methods (see text for explanations).