Improved Image Quality of Time Resolved Contrast Enhanced MRA using Compressed Sensing, Parallel Imaging and Singular Value Threshold

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TARGET AUDIENCE: Accelerated imaging and reconstruction techniques.

PURPOSE: Time-resolved 3D contrast-enhanced MR angiography (TR CE-MRA) often requires highly accelerated image acquisition to achieve clinically desired temporal and spatial resolutions. Combination of VIPR acquisition with improved multi-channel coils and advanced reconstruction techniques such as Parallel Imaging (PI) and Compressed Sensing (CS), offers substantially greater acceleration than past methods. However, image quality is restricted by poor SNR due to the limited amount of data used for reconstruction. In this work, we explore the temporal similarity of TR CE-MRA to further improve the SNR and image quality.

METHODS Undersampled 3D radial acquisition (VIPR) with bit-reverse projection ordering was utilized as the sampling scheme for TR CE 3D MRA. Read out points were 256 per projection with 13920 total projections. Data were first reconstructed using L1-norm regularized SENSE with medium regularization levels (CS-PI). Obtained images were then vectorized into a spatial-temporal matrix *L*,

$$L = \begin{bmatrix} \vec{l}_1 & \vec{l}_2 & \ldots & \vec{l}_N \end{bmatrix} = \begin{bmatrix} l(x_1,t_1) & \ldots & l(x_1,t_N) \\ \vdots & & \\ l(x_M,t_1) & \ldots & l(x_M,t_N) \end{bmatrix}$$

Each column vector $\vec{l}_i$ corresponds to image at time frame i, and the rows of *L* correspond to temporal dynamics of image voxels. For TR CE-MRA, the temporal dynamics of voxels are similar. Namely, the rows of this *MxN* matrix are linearly dependent and thus the rank (r) of matrix *L* should be low (*r<<min(M,N)*). Therefore, if a Singular Value Decomposition (SVD) is applied to the matrix *L*, the singular values rapidly drop after a certain term T. Our hypothesis is that the small singular values corresponds to noises in TR CE-MRA and a thresholding technique can be applied to the singular values to generate noise reduced image frames. This technique is referred to as singular value threshold (SVT).

The proposed reconstruction method (CS-PI-SVT) has been retrospectively applied to five TR CE MRA datasets acquired using VIPR sampling scheme from patient volunteers with intracranial vascular disease. Image quality was assessed by comparing SNR, waveform, and visibility of small vessel structures to the images reconstructed using CS-PI only**.**

RESULTS All datasets have been reconstructed successfully using the proposed CS-PI-SVT method. SVT threshold was set to 4 for all cases. Images with SVT show improved SNR and vessel delineation. Five pairs of ROIs were chosen at various vessels and surrounding background from each reconstructed series for SNR measurement. SNR was improved by factor of 1.9±0.6 with the SVT algorithm. Figure 1 shows an image comparison between CS-PI and CS-PI-SVT. With the SVT de-noise technique, small vessels can be better depicted as shown by arrows. Waveform comparison before and after the SVT algorithm is demonstrated in Figure 2. SVT reduces signal fluctuation due to noise whereas maintains the contrast dynamics.

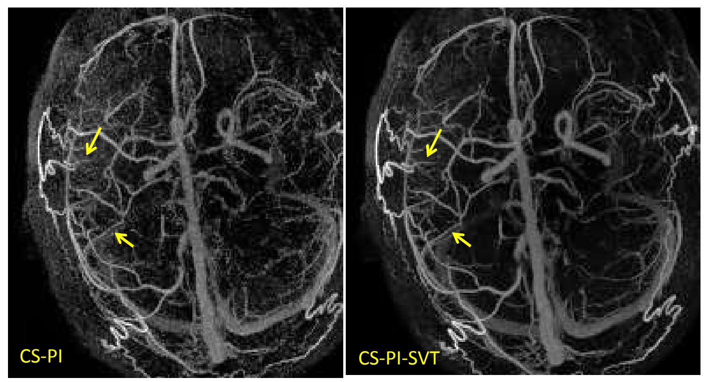

Figure 1 Image comparison between CS-PI (left) and CS-PI-SVT (right). Arrows show the improved small vessel delineation with SVT algorithm.

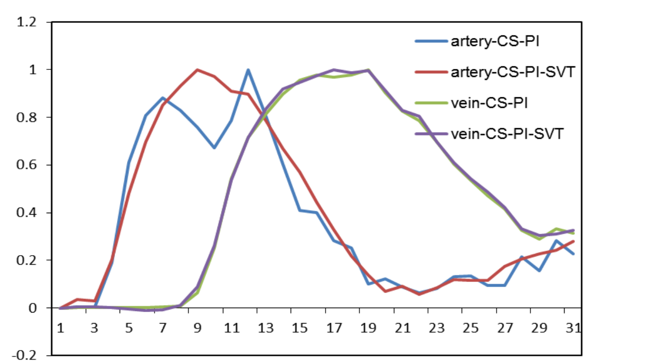

Figure 2 Waveform comparisons between CS-PI and CS-PI-SVT.

DISCUSSION AND CONCLUSION For iterative reconstruction of highly undersampled data, i.e. VIPR with CS-PI, image quality strongly depends on the selection of regularization strength. The fewer sample we have, the stronger regularization is required. Concomitantly, the risk of losing vessel details increases as well. In current implementation, SVT was utilized as a supplemental noise reduction technique after CS-PI, such that vessel details can be better preserved with medium level regularization in CS-PI and improved SNR from SVT provides better vessel delineation. Alternatively, the low rank property can also be introduced as part of the regularization in the iterative reconstruction. Phantom studies will be conducted to quantify the performance.

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