

Resolution improvement of 3D DCE-MRI using dynamic CS with patch-based non-convex low rank k penalty

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Purpose: One of important applications of dynamic contrast-enhanced (DCE) MRI is to observe brain tissue dynamics. In this work, we applied a dynamic compressed sensing (CS) with patch-based non-convex low-rank penalty¹ for 3D DCE-MRI to exploit temporal redundancy of the dynamic images to improve the spatiotemporal resolution of the conventional GRAPPA² reconstruction. Experiments show that the proposed method provided improved spatio-temporal resolution than GRAPPA reconstruction.

Methods: We use a scanner provided sampling pattern, which is designed to sparsely sample k-space data in interleaved fashion to conserve spatial and temporal resolution in the reconstructed image while reducing the acquisition time³. Specifically, each k-space data is sparsely sampled as shown in Figure 1. Sample positions at time 1 and 2 are used to record the positions of center and high-frequency regions. In the conventional reconstruction, from time 3, missing k-space locations of each 3D data are filled with k-space in adjacent 3D data while maintaining central k-space data. After filling the missing k-space, each coil image is reconstructed using GRAPPA.² This method, however, sacrifices the temporal resolution due to the sliding window operation. Instead, this paper proposes a direct dynamic CS reconstruction by exploiting the self-similarities. More specifically, only the k-space data corresponding to each time frame are used in the proposed reconstruction to improve the temporal resolution (Figure 1). To deal with the ill-posedness from the missing k-space data, we use CS MRI with patch-based low rank penalty. Specifically, as shown in Figure 1, we collect a group of patches and impose a non-convex rank penalty using a generalized Huber function³ by exploiting that the patches at the same spatial locations have similar geometric structures along time even though their magnitudes may change along time in DCE-MRI. To deal with the non-convexity of rank penalty, our optimization problem is represented as an augmented cost function using Legendre-Fenchel transform such that $C(W, x) = ||y - Fx||^2 + \sum_p \lambda_p \{ \frac{1}{\mu} ||V_p(x) - W_p||_F^2 + ||W_p||_{g_{\mu, \nu}} \}$. Here, y is a k-t space data, F is a 2-D Fourier sampling operator, and x is an unknown spatiotemporal image to reconstruct. Reconstructed GRAPPA image was used as an initialization for facilitating the search of similar patches, enabling fast reconstruction with the small number of iterations. The optimization problem was then solved by an alternating minimization with respect to $\{W_p\}$ and x for each coil and the sum-of-squares images are calculated.

Results: 3D DCE data with downsampling rate $R > 5$ (Figure 1) was acquired on a Siemens 3T Verio scanner at Seoul National University Hospital, Korea. Acquisition parameters are as follows : 192x252 matrix size, 40 partition encoding lines, TR/TE 2.81/1.04 ms, slice thickness 3 mm, 32 channels and 60 time frames. Figure 2 shows the sum of squared (SoS) images at the 21st partition encoding line. First column of Figure 2 shows FoV images. The proposed dynamic CS with patch-based low-rank regularization along temporal dimension shows clear reconstruction than GRAPPA only. The second column images show magnified views and two pixel positions A and B are designated. Temporal variation plot at position A shows that the proposed method provides much smoother dynamics than GRAPPA only. B is at the area where intensity change is insignificant. The temporal plot of the pixel at B implies that the proposed method is quantitatively more accurate than the conventional GRAPPA reconstruction.

Conclusion: In this work, dynamic CS using patch-based low-rank regularization is used for dynamic 3D DCE-MRI. Experimental results imply that the proposed method was effective for denoising and improved spatio-temporal resolution of GRAPPA reconstruction.

References: 1. Yoon H, et al. ISMRM 2013, p3803; 2. Griswold M, et al. MRM, 2002, 1202-1210; 3. Chartrand R, et al. IEEE Trans Sig Proc 2011;

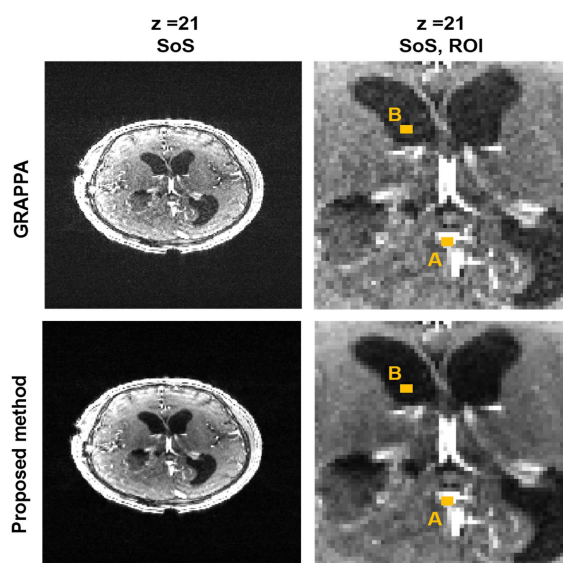


Figure 2. Reconstruction images using GRAPPA and the proposed method. In region of interest (ROI), two pixels (A,B) are indicated and their temporal variations are indicated in the graphs.

