

IMPROVED BALANCE OF ARTIFACT/NOISE LEVEL AND FINE STRUCTURE PRESERVATION IN HIGHLY ACCELERATED PPI

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Target Audience

Scientists and clinicians interested in highly accelerated MRI.

Purpose

Based on spatial sensitivity of coil arrays, Partially Parallel Imaging (PPI) [1] has been widely used in clinical practice to accelerate acquisition, but at the cost of reduced Signal-to-Noise Ratio (SNR). Often, regularization schemes are used to preserve SNR. However, existing regularization schemes have the difficulty to balance the reduction of artifact/noise level and the preservation of boundaries and fine structures, especially when the acceleration factor is high. The purpose of this work is to achieve low noise/artifact level with minimal impact on fine structures at high acceleration factors. Preliminary results demonstrated that lower root-mean-square-error (RMSE) and better preserved fine structures can be achieved by using the proposed method than CS-SENSE [2]. Low errors image was reconstructed at acceleration factor as high as 8 with an 8-channel head coil.

Methods

Patch-wise non-local sparse [3,4]: The transform domain determines the sparsity, and is the key to compressive sensing based denoising. In patch-wise non-local sparse, the transform domain is the clustered image fragments (patches) according to the similarity to exemplar patterns. In this work, we adopt low-rank as the sparsity constraint onto the transform domain to exploit the correlation among similar patches.

Combination with PPI: To combine patch-wise non-local sparse with sensitivity encoding (SENSE), the following objective function was proposed:

$$I = \arg \min_I \sum_{j=1}^{Nch} \|F_p(S_j I) - k_j\|_F^2 + \tau \sum_{m,n} \|R_{m,n}(I)\|_* \quad (1)$$

where $R_{m,n}(I)$ stands for the group of similar patches whose exemplar patch is located in (m,n), and its nuclear norm measures the correlation within the group. Other notations follow the definition in [5]. To solve (1), a Split Bregman iterative scheme is exploited.

Experimental setup: Comparison with CS-SENSE (using total variation (TV) as regularization) on brain data was performed to illustrate the advantage of proposed method. T2-weighted axial brain data were acquired on a Philips 3T system (Philips Healthcare, Best, the Netherlands) with an 8-channel head coil (Invivo Corp, Gainesville), Phase encoding direction was left-right. All k -space were fully acquired and then artificially down-sampled to simulate partial acquisition. Pre-scanned low resolution coil sensitivity maps were used in reconstruction. Both 1-D acceleration along PE direction and Poisson-Disc (to simulate 2-D acceleration in 3-D imaging) were used.

Results

Fig.1 and Fig.2 show the experiment results. Fig.1 compares the reconstructed images by our proposed method with CS-SENSE on head data, the reconstruction RMSEs were listed at the bottom. Fig.2 compares the reconstruction RMSEs at different acceleration factors for both methods.

Discussion

Experimental results demonstrate that, compared with CS-SENSE, the proposed method achieves lower RMSEs and more importantly, much better preserved boundaries and fine structures, especially at high acceleration factors, which could be clearly seen in the difference images in Fig.1. The advantage is realized due to the improved regularization term, which can preserve boundaries and fine structures better while sufficiently reduce noise level.

Conclusion

We present a new regularization scheme for highly accelerated PPI, with better balance of SNR and fine structure preservation compared with CS-SENSE. In-vivo results implicate the great potential of patch-wise non-local sparse to highly accelerate acquisition while preserving the image quality in clinical practice.

References :

[1] Pruessmann MRM 1999;42(5):952-962 [2] Liang D, et al., Magn Reson Med 2009;62(6):1574-1584 [3] Weisheng Dong et al., IEEE TIP, preprint [4] J. Mairal et al., ICCV, 2009: 2272–2279 [5] Feng Huang et al. MRM, 2010;64:1078-1088

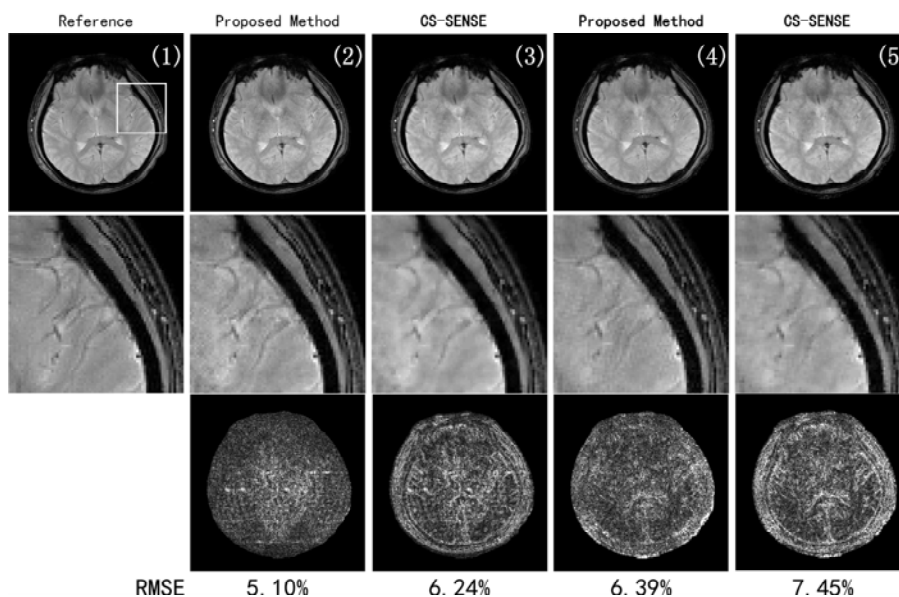


Figure 1. Reconstructed images with zoomed-in pictures and difference maps (with respect to the reference which was reconstructed with fully k -space, brightened 10 times): (1) full k -space; (2)~(3) equally spaced, net reduction factor=4; (4)~(5) Poisson Disc, net reduction factor=8.

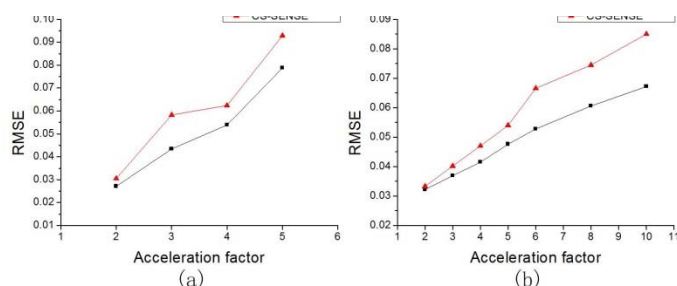


Figure 2. Reconstruction RMSEs at different acceleration factors: (a) Equally spaced sampling; (b) Poisson-Disc sampling