Compressed Sensing Parallel Imaging

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Introduction

Both parallel MR Imaging (pMRI) and compressed sensing (CS) can significantly reduce image acquisition time in MRI, the former by utilizing multiple channel receivers and the latter by utilizing the sparsity of MR images in a transformed domain [1,2]. Generally speaking, pMRI can be formed as an inverse problem, where the reconstruction can suffer from the poor numerical condition and residual aliasing. In our study, CS is used as a regularization tool to improve the pMRI reconstruction. Reconstruction results from *in vivo* data show that CS can significantly suppress the aliasing artifacts and improve SNR with very minor resolution loss in pMRI. The new method is shown to perform better than the truncated singular value decomposition (SVD) and the Tikhonov regularization.

Methods

The imaging equation in pMRI can be formed as $y = Ax$, where y is a $(n_a \times n_c) \times 1$ vector of the multi-channel k-space data where n_a is the number of subsampled data per channel, n_c is the number of receiver channels, A is a $(n_a \times n_c) \times N$ forward matrix which incorporates the gradient-induced and sensitivity encodings where N is the image size, and x is $N \times 1$ desired image vector. In the conventional image-space reconstruction, x is solved using the least squares solution. In the new method, CS regularization solves the reconstruction problem by minimizing $||Ax-y||_2+\lambda_1||wx||_1+\lambda_2 TV(x)$. The first term is the data fitting error between Ax and y, the second term quantifies the sparsity of x using the transform matrix w (e.g., in the wavelet domain) based on the L1 norm, and the last term imposes some level of continuity on x using total variation. Two other regularization methods were compared: 1) truncated SVD with a cutoff threshold of 5% of the maximum eigenvalue [3]. 2) Tikhonov regularization which minimizes $||Ax-y||_2+\beta||x||_2$ [4]. All algorithm was implemented in Matlab based on the sparseMRI and PULSAR [5,6].

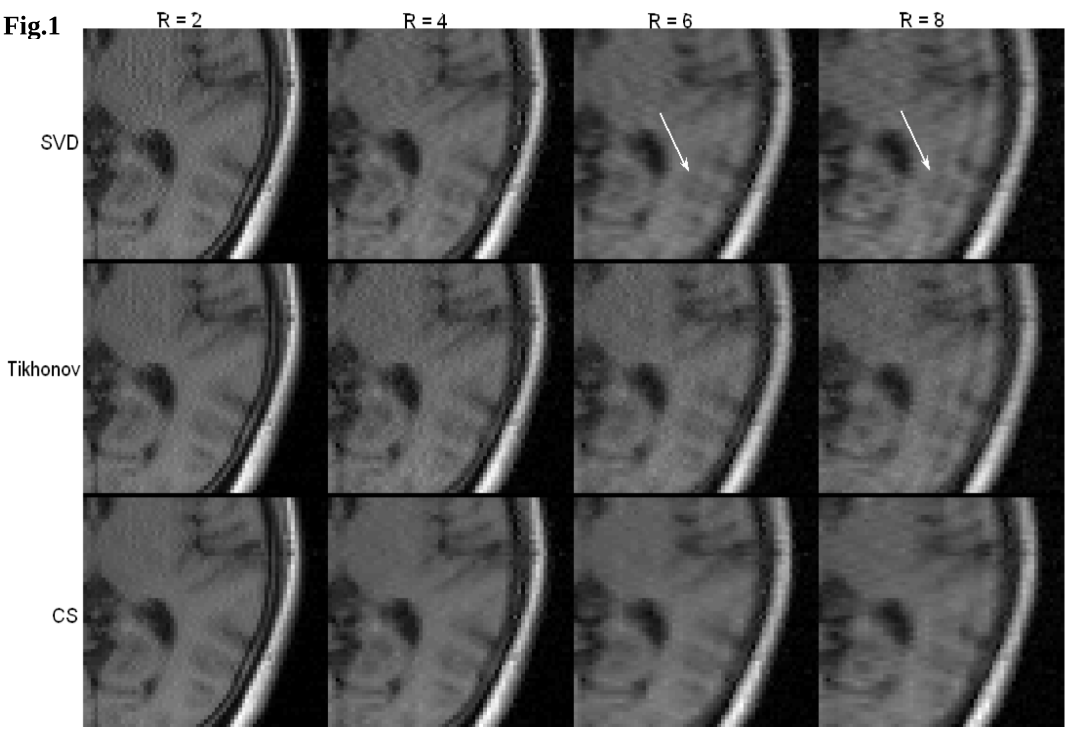
To test the algorithm, a set of brain data (128 encodings) were acquired on a healthy volunteer on a 1.5 T scanner using an 8-channel head array coil and fast spin-echo sequence. A separate data set acquired using a fast gradient-echo sequence was used for coil sensitivity calibration. The phase encodings were retrospectively decimated using a variable density mask (dense in the center and sparse in the outer) to achieve desired reduction factors (R) from 2-8. Reconstruction of the above three methods were performed and compared visually, and SNR was measured. Regularization parameters were manually chosen (λ_1=0.07, λ_2=0.02, and β=0.4, respectively) from visual inspection.

Results

Figure 1 shows the reconstructed images from three methods at different reduction factors. Truncated SVD reconstruction shows significant aliasing artifacts (see arrows in first row for R = 6 and 8). The Tikhonov method can smooth the images to some extent but is still affected by artifacts and noise. In contrast, the new method suppresses residual aliasing artifacts as well as noise, but shows some minor resolution degradation, particularly when large TV regularizations is used (not shown).

Figure 2 compares the SNR of the three reconstruction methods. The SNRs are computed as the ratio between average strength of region S and standard deviation of the region N shown in the right image. The CS improves SNR at all reduction factors, but the maximal enhancement is R = 8 (4 dB as compared to the SVD method).

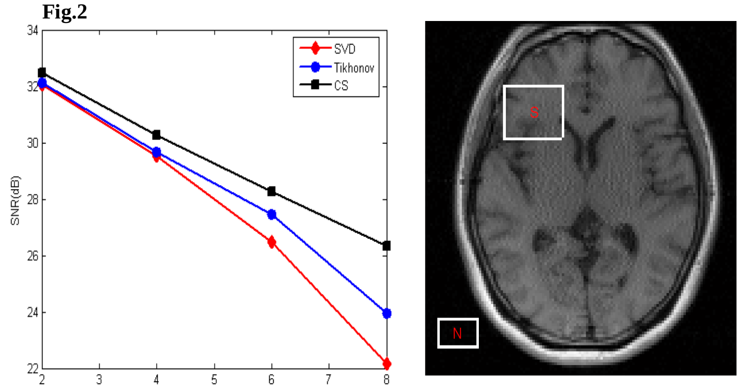
Fig.1



Discussion

Incorporating the sparsity of MR images in the regularization method can further improve reconstruction in pMRI. The CS method has the potential to eliminate residual aliasing artifacts and suppress noise but it also tends to have minor resolution degradation. Significant problem remains, for example, how to individually and jointly optimize the regularization parameters, the sparsifying transform, and subsampling pattern to improve reconstruction results.

Fig.2



References

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