Null Space Imaging with Compressed Sensing for Rapid Parallel Imaging

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Introduction: Null Space Imaging (NSI) utilizes higher-order gradients for spatial encoding that are tailored to complement the receiver coil spatial information in order to maximize data efficiency to allow high acceleration factors.[1, 2] Another acceleration technique, compressed sensing (CS), exploits assumed sparsity of MR images in the wavelet domain by sampling k-space in a random density-compensated manner and applying a non-linear reconstruction algorithm. Both NSI and CS focus on collecting data in a targeted manner. Previous work with orthogonal multi-polar gradients demonstrated parallel CS with non-linear gradients, albeit with artifacts particular to the imaging method.[3] Since CS effectively dampens coherent aliasing, we hypothesized that when CS is applied to NSI it would efficiently reduce aliasing artifacts and spread residual artifacts more incoherently than comparably undersampled k-space trajectories using only linear gradients. Therefore, the current work proposes a synergistic NSI CS with total variation (TV) constraint approach for suppression of parallel imaging artifacts at high acceleration factors.

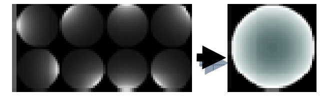

Figure 1a. Eight element microstrip array coil

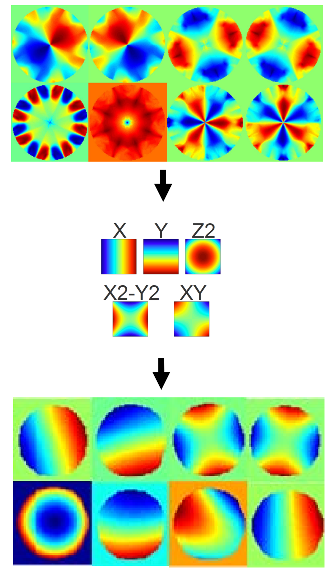

Figure 1b. In NSI, imaging gradients are tailored to receive coil profiles and approximated with spherical harmonics

Method: Sparsity theory dictates it is possible to reconstruct an image represented by an n-dimensional complex vector **x** that is sparse in a transform domain.[4] In both the CS and NSI approach, the imaging system may be treated as an equation **y** = **Ax**, and reconstruction proceeds from the same theoretical base. In any parallel imaging CS approach, the additional n_c factor of data collected from the parallel receive coils better conditions the inversion of the encoding matrix **A.** NSI converges on the solution through the Kaczmarz iterative algebraic projection reconstruction algorithm.[5] The CS approach proceeds through a L1-penalized norm non-linear conjugate gradients (nlCG) solution of the convex minimization problem: $\mathrm{Phi}(x) = \|A^* W'^* x - y\|^2 + \lambda_1 * |x|_1 + \lambda_2 * TV(W'^* x)$ as implemented by Lustig.[6] Firstly, we note that the W represents the Daubechies wavelet transform, a domain in which the image is sparse. The imaging system **A** now includes an NSI acquisition scheme in which the gradients are selected from the ordered singular vectors of the coil phase null space. The resulting NSI gradients are designed to complement parallel receive coils. The nlCG algorithm must now use the Kaczmarz algorithm to calculate the objective function derivatives. For NSI gradients, the first and second order non-degenerate in-plane spherical harmonics form the gradient shapes. The number of samples per readout was simulated at Ns = 512 which required proportionally increasing the gradient strength at fixed sampling window as per the Nyquist sampling theorem. Extra encoding is provided along the variation of each gradient shape. Whole body noise was injected at 5% at the Ns=128 level and then scaled up by the root of the sampling factor, eg. 10% noise fraction for a 512 samples per readout acquisition. The receiver coils are simulated from a microstrip array coil.[7] Simulations were compared via sum-of-squares error (SSE).

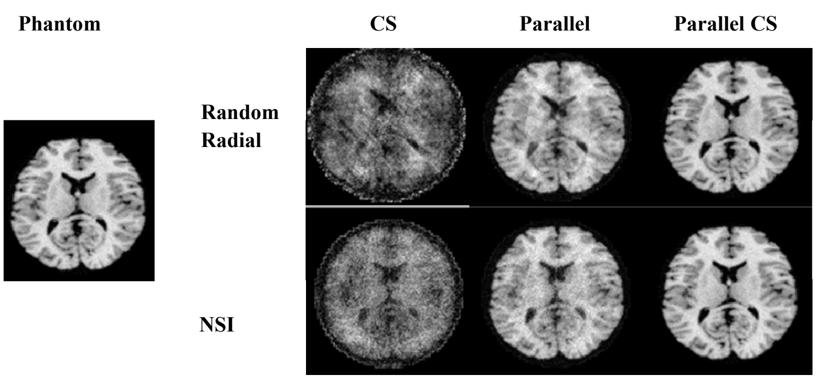

Figure 2. Comparison of compressed sensing, parallel, and compressed sensing parallel simulations at R =16.

Results: Reconstructed 2-D images compare NSI, random parallel radial, and random variable density k-space phase encodes on a brain phantom and numerical phantom at an acceleration of R=16. The simulations demonstrate that CS-NSI reduces the SSE compared to the other methods. With the random angle parallel radial acquisition scheme, the compression algorithm does not fully recover features, and a blur is observed. The lower SSE of the NSI method manifests as a reduced granularity and blur.

Discussion: CS and NSI are complementary methods that allow further accelerations in parallel imaging. NSI, which utilizes imaging gradient complementarity with receiver coil sensitivity profiles and CS, which relies on sparsity, are methods which collect data more efficiently and disperse residual aliasing artifacts making them less apparent. Current challenges for such an approach include calibration of experimental imaging gradients and parallelized GPU implementation of image reconstruction, both of which are currently underway.

References: [1]Stockmann et. al. Magn Reson Med. 2010. 64: p. 447-456. [2]Tam L.K.., et al., Proc. Intl. Soc. Magn. Reson. Med., 2010, p.2868. [3] Lin F-H. et. al. Proc. Intl. Soc. Magn. Reson. Med., 2010, p.546. [4]Candes E, et. al. IEEE Trans Inf Theory 2006;52:489–509. [5]Herman G.T. et. al. J. Theor. Biol. 42:1. [6]Lustig M., et al. Magn Reson Med. 2007. 58: p. 1182-1195. [7]Lee, RF, et. al. Magn. Reson. Med 2004; 51:172.
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