Region of interest compressive sensing (ROICS)

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Introduction: Compressed sensing (CS) provides for reconstruction of data from highly undersampled measurements (1). This has been used in MRI to gain acceleration in acquisition time and has been demonstrated on MRI methods (2). CS performance depends significantly on sparsity of the image data (1,2) in a transform domain and determines the number of measurements to be made for exact reconstruction (1) (sparser the data, fewer the number of measurements required for reconstruction and hence increased acceleration). The current work aims at providing additional sparsity than the conventional CS approach regardless of the transform chosen to achieve increased acceleration, using a novel technique called "Region of Interest Compressed Sensing" (ROICS).ROICS is based on the hypothesis that superior CS performance can be obtained by limiting the CS reconstruction to a ROI.This restriction is justified in applications where the anatomy of interest for further analysesinvolves a ROI. The inclusion of such a ROI mask in the functional of the CS convex optimization problem enhances sparsity in the reconstruction by decreasing the number of non-zero coefficients, which implies a reduction in the number of k-space samples required for reconstruction. This should result in acceptable reconstructions at higher accelerations as compared to conventional CS.

Theory: The conventional CS implemented in unconstrained formis described by: $\min_m(\| F_u(m) - y \|_2 + \lambda \| \psi(m) \|_1)$ [1].Here, *m* is the estimate of the image to be reconstructed, F_u is the undersampled Fourier operator (*F(.)** Undersampling mask), *y* is the undersampled k-space measured by the acquisition process, λ is the regularization factor determined by Tikhonov regularization or an L-curve, Ψ is the sparsifying transform operator, $||.||_k$ is the k-norm operator. Equation [1] can be re-written as: $\min_m(\| F^{-1}(F_u(m) - y) \|_2 + \lambda \| \psi(m) \|_1)$ [2], where F^{-1} is the inverse Fourier transform. The data consistency term is evaluated in the spatial domain as opposed to the k-space domain and is equivalent to eq. [1].The unconstrained CS problem in eq. [2] can be solved for a particular ROI and can be derived from eq. [2] by weighting the spatial data consistency term over a ROI, described by a diagonal matrix W of size (Ns x Ns), where Ns is the product of the number of columns and number of rows of the image. Such spatial weighting has also been used elsewhere (3). Increasing the sparsity using a ROI would result in better reconstructions at higher accelerations compared to conventional CS reconstructions with identical regularization factors and sparsity transforms**.**

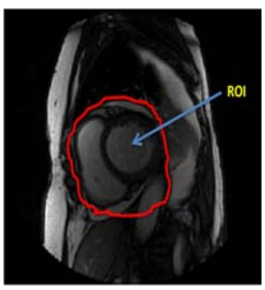

Figure 1: A representative cardiac frame showing achosen ROI in red (at 1X)

Methods: ROICS technique was applied to 10 cardiac frames (magnitude images) selected from 10 different datasets with similar anatomy. Complex white noise (standard deviation=0.05) was added to the selected frames that were then reconstructed retrospectively after undersampling the resulting k-space data obtained from these noise-incorporated magnitude images at factors of 0.5, 0.33, 0.25, 0.2, 0.125, 0.1 equivalent to 2x, 3x, 4x, 5x, 8x, 10x acceleration using the conventional CS technique as in eq. [1] and ROICS as in eq.[3].The ROI was drawn to include only the heart and neighbouring structures. Figure 1 depicts a representative cardiac frame reconstructed using full k-space data (without noise addition for reference)with the red outline depicting the chosen ROI. The error of reconstruction was quantified by the normalized root mean square error (NRMSE) metric with the 1X reconstruction as the reference. Average NRMSE values for 10 frames at different accelerationswere calculated for both conventional CS and ROICS.

Results: The results of reconstruction for the representative data in figure 1, obtained using the two techniques, can be observed in figure 2. It can be observed that conventional CS and ROICS perform similarly at lower acceleration factors of up

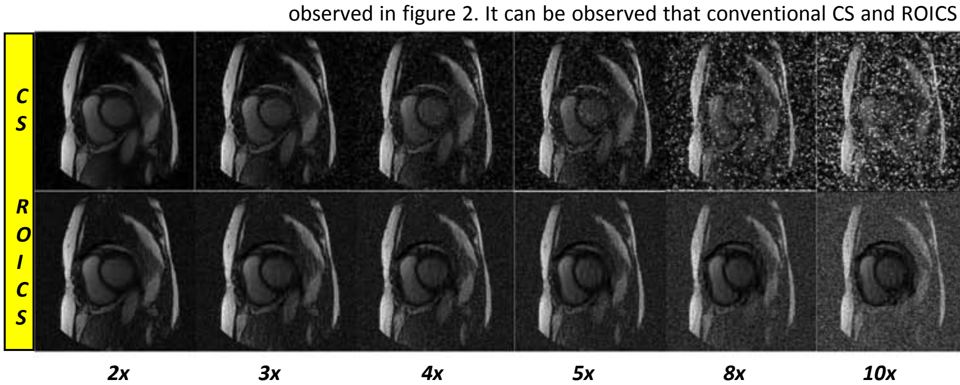

Figure 2: Conventional CS and proposed ROICS technique at different acceleration

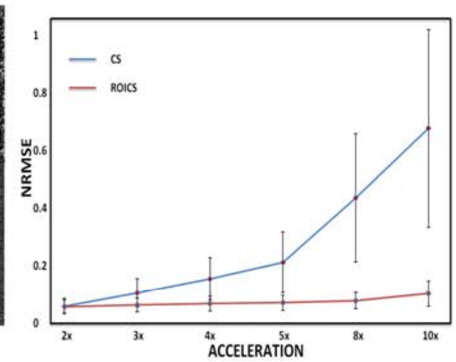

Figure 3: NRMSE Comparison

to 4X. However, it can be seen that the ROICS outperforms conventional CS at acceleration factors of 5X and beyond. The noise outside the ROI in ROICS demonstrates the effect of spatial weighting in eq. [3].The resulting ROICS reconstruction with 10% of the data shown in figure 2 (lower panel) demonstrates the utility of the proposed approach. The graph in figure 3 shows a significant increase in the NRMSE value after 5x acceleration using conventional CS as compared to corresponding values computed for ROICS reconstructions.

Conclusion&future work: The application of ROICS has been performed here for the first time. ROICS allows for increasing the sparsity required for CS reconstructions by decreasing the number of non-zero coefficients to be estimated. It has been demonstrated qualitatively and quantitatively that ROICS outperforms CS at higher acceleration factors. Current and future work involves prospective application of ROICS and optimization of k-space trajectories for ROICS and subsequent combination with parallel imaging. The applicability of ROICS can be easily extended to other MRI acceleration tasks where a ROI can be well defined and is permissible. An example of such an application is renal angiography at 7T where the regions outside the ROI could be severely affected by field inhomogeneities and might not be of interest to subsequent analyses. **References:** 1)Candes et al., IEEE Trans. Inform Theory 2006 2) M. Lustig et al., MRM, 2007.3) Grissom et. al., MRM, 2006. **Acknowledgement:** P41 EB015894