ROICS-PI:Combination of Region of Interest Compressed Sensing and Parallel Imaging for Arbitrary k-space Trajectories to Achieve Highly Accelerated MRI

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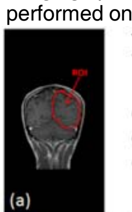
Introduction: Compressed sensing (CS) (1) and Parallel Imaging (PI) (2) are two well-known approaches in MRI to accelerate image acquisition. Combination of CS and PI results in increased performance than using either of them individually and this combination has been demonstrated on MRI methods (3, 4). In this work, a recently developed technique called "Region of Interest Compressed Sensing (ROICS)" (5) is combined with PI to provide superior performance as compared to CS-PI. CS reconstruction performance depends on data sparsity (6) and hence sparser the data, better would be the CS reconstruction. Increased sparsity can be achieved by limiting CS reconstruction to a region of interest (ROI) rather than the entire image. In parallel imaging, multichannel receiver arrays are used to acquire the MR signal simultaneously from several receiver coils that provides significant increase in imaging speed. However, PI is also Signal to Noise Ratio (SNR) dependent and hence is limited in cases of low SNR acquisitions. ROICS reconstruction performed on each channel will exploit data sparsity that would result in increased SNR through removal of incoherent noise in the ROI and hence provide for a better input for the subsequent PI based reconstruction.



Theory: Unconstrained convex optimization functional for conventional compressed sensing can be represented by $\min_m(\| F_u(m) - y \|_2 + \lambda \| \psi(m) \|_1)$ [1]. Here, *m* is the current estimate of the image to be obtained, 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 L-curve, Ψ is the sparsifying transform operator and $\|.\|_k$ is the k-norm operator. The unconstrained compressed sensing problem in [1] can be solved for a particular ROI with the data consistency evaluation performed in the image domain. 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 and is equivalent to [1]. Equation for ROICS can be derived from equation [2] by weighting the spatial data consistency term over a region of interest, described by a diagonal matrix W of size (Ns x Ns), where Ns is Number of columns x Number of rows of the image. This results in: $\min_m(\| F^{-1}(F_u(m) - y) * W \|_2 + \lambda \| \psi(m) \|_1)$ [3]. Data samples required for reconstruction is reduced by increasing the sparsity achieved through the application of the ROI mask '*W*' and this would hence result in better reconstructions at higher accelerations compared to conventional CS reconstructions. Data acquired using multi channel coils simultaneously could be ROICS reconstructed per channel and then PI reconstructed to yield the final image. We can rewrite the equation [3] for each channel *'c'* with an arbitrary k-space trajectory to perform ROICS-PI $\min_m\left(\| F_1{}^{-1}(F_{1u}(m_c) - y_c) * W \|_2 + \lambda \| \psi(m_c * W) \|_1\right)$ [4]. Here, F_{1u} is Non Uniform Fast Fourier Transform (NUFFT) for arbitrary k-space applied on image estimate m_c and y_c is the k-space of the c^{th} channel. These channel images are then reconstructed using equation [26] in ref. (7), reproduced here $(IE^H DEI)b = a$ [5], where, *a* is the intermediate image, *b* is an approximation solution, *I* is intensity correction, *E* is the NUFFT of the coil sensitivity weighted image resulting in k-space, E^H is complex conjugate transpose of E and D is the density compensation factor.

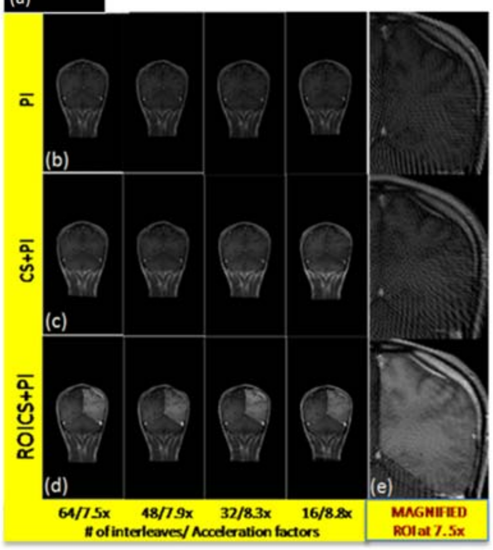


Figure 1:Reconstructed Images: (a): ROI drawn on Original/SoS image, (b): PI reconstruction, (c): CS+PI reconstruction, (d): ROICS+PI reconstruction, (e): ROI magnified image at 7.5x acceleration to compare proposed method with existing method

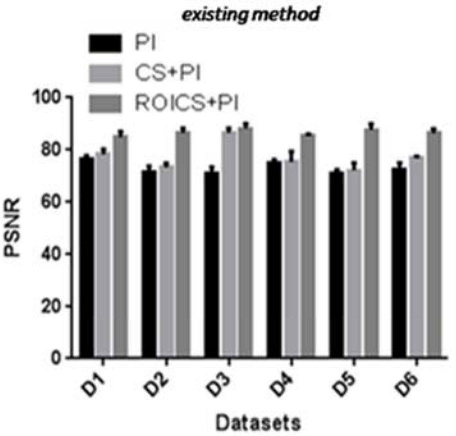


Figure 2: PSNR Comparison (Data set 1 to Data set 6) for 3 methods

Methods: ROICS-PI technique was applied on 6 human brain datasets acquired using a 1.5 T Siemens scanner, as part of an ERB approved protocol, in coronal orientation and a spin echo sequence using 6 receiver coils (TR/TE = 410/8.7ms, matrix size=512 x 256) with no CS or PI during acquisition. ROICS was applied to each channel data by selecting a common region of interest across all channels (marked in red in figure 1(a)) after retrospectively undersampling k-space data with a variable density spiral trajectory consisting of 64, 48, 32 and 16 interleaves. Images were reconstructed at these values of interleaves corresponding to acceleration factors of 7.5x, 7.9x, 8.3x and 8.8x, using PI, CS+PI and ROICS+PI methods on six channel data to compare proposed method with these existing methods. The reconstruction error for the proposed method and the existing methods were quantified by Peak SNR (PSNR) using the formula: $PSNR = 20log_{10}\left(\max(y)/\sqrt{sum(x-y)^2}\right)/N$ [6] where, x was the fully sampled original image and y was the reconstructed image and N was the size of the image. Average PSNR value was calculated for 6 data sets at different interleaves/acceleration factor to compare the proposed method with the existing methods. **Results and Discussion:** The sum of squares (SoS) of the channels image with the ROI chosen for reconstruction is shown in figure 1 (a) for a representative data set. The results for the three methods over the 4 acceleration factors are shown in figure (b) PI only, (c) CS+PI (d) ROICS+PI. It can be observed from these figures that ROICS+PI performs qualitatively better than the other 2 methods. Figure 1(e) depicts the magnified ROI at 7.5x depicting aliasing artefacts that can be observed in the other 2 methods arising due to the spiral trajectory while ROICS+PI is able to reconstruct the image with significantly reduced aliasing artefacts. At acceleration values above 7.5x, it can also be observed that ROICS+PI has the least artefacts in the chosen ROI. The graph in figure 2 shows the PSNR for proposed and conventional reconstruction techniques for 6 data sets and it can be noted PSNR value of proposed method is higher compared to the other two techniques in case of each data for the specified ROI.

Conclusion and future work: Combination of ROICS and PI has been proposed and performed for the first time. It can be observed from the figures 1 and 2 that the proposed method performs better than the other two methods qualitatively and quantitatively. The technique has been implemented for arbitrary k-space trajectories and hence provides a general framework. Current and future work involves optimizing k-space trajectories to suit specific ROI shapes and identification of specific MR applications, integrating it in the reconstruction framework.

References: 1) M. Lustig et al., *MRM*, 2007. 2) Larkman et al., Phys. Med. Biol. 2007. 3) Kim et al., IEEE ICASSP 2009. 4) Murphy et al., IEEE TMI 2011.5) Konar et. al., ISMRM pp. 3801, 2013.6) Candes et al., IEEE Information Theory 2006. 7) Pruessmann et al., *MRM,* 2001