Application of Region of Interest Compressed Sensing to Accelerate Magnetic Resonance Angiography

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***Abstract*— Magnetic Resonance Angiography (MRA) is a group of techniques based on Magnetic Resonance Imaging (MRI) to image blood vessels. Compressed Sensing (CS) is a mathematical framework to reconstruct MR images from sparse data to minimize the data acquisition time. Image sparsity is the key in CS to reconstruct MR images. CS technique allows reconstruction from significantly fewer k-space samples as compared to full k-space acquisition, which results in reduced MRI data acquisition time. The images resulting from MRA are sparse in native representation, hence yielding themselves well to CS. Recently our group has proposed a novel CS method called Region of Interest Compressed Sensing (ROICS) as a part of Region of Interest (ROI) weighted CS. This work aims at the implementation of ROICS for the first time on MRA data to reduce MR data acquisition time. It has been demonstrated qualitatively and quantitatively that ROICS outperforms CS at higher acceleration factors. ROICS technique has been applied to 3D angiograms of the brain data acquired at 1.5T. It helps to reduce the MRA data acquisition time and improves the visualization of arteries. ROICS technique has been applied on 4 brain angiogram data sets at different acceleration factors from 2x to 10x. Reconstructed images show ROICS technique performs better than conventional CS technique and is quantified by the comparative Signal to Noise Ratio (SNR) in the ROI.**

I. INTRODUCTION

MRI is a biomedical imaging modality that provides images with excellent soft tissue contrast. MRI can extensively be used to image detailed structure, function and metabolism of the organ of interest. A significant disadvantage of MRI is slow acquisition of data as compared to other imaging modality such as Computed Tomography (CT) and Positron Emission Tomography (PET). CS [1, 2] is a mathematical framework which has made a significant impact in the field of MRI through minimization of data acquisition time. CS technique allows to use significantly fewer k-space samples to reconstruction as compared to full k-space acquisition. As sparsity increases, CS provides better reconstruction at increased accelerations for transformed sparse domain [3] and it has been demonstrated on various MRI methods such as dynamic MRI to achieve acceleration [4].

MRA is a group of techniques based on MRI to image blood vessels used in order to evaluate them for stenosis (abnormal narrowing), occlusion or aneurysms (vessel wall dilatations, at risk of rupture). Angiograms are sparse in pixel domain (spatial) and are hence suitable for CS reconstruction. Unlike a traditional angiogram, which requires inserting a catheter into the body, MRA is a far less invasive, less painful procedure and it does not involve exposure to radiation. MRA is used to examine blood vessels in key areas of the body, including the brain, neck, heart, chest, abdomen (such as the kidneys and liver), pelvis, legs and feet, arms and hands.

ROICS [5] is a novel technique which allows for increasing sparsity required for CS reconstructions by decreasing the number of non-zero coefficients to be estimated. ROICS is based on the hypothesis that superior CS performance can be obtained by limiting the CS reconstruction to a ROI of relevance. This relaxation is justified in most applications where the anatomy of interest such as that for MRA has a surrounding structure and the background is typically not important for further analysis. To achieve short acquisition time, techniques like parallel imaging (PI) [6] and other undersampling strategies such as keyhole imaging have been used. These techniques are governed by the Nyquist sampling rate and hence cannot yield acceleration beyond the Nyquist limit due to the resulting aliasing artifacts.

II. THEORY

A. CS and ROICS

CS technique is efficiently used for acquiring and reconstructing an image by finding a solution to an underdetermined system. This gives the images sparseness or compressibility in transform domain, allowing original image to be reconstructed by relatively few measurements. ROICS limits CS to a ROI and it can be derived from the unconstrained convex optimization functional formula for conventional CS which is represented by (1)

$$min_m(\|F_u(m) - y\|_2 + \lambda \|\psi(m)\|_1) \tag{1}$$

where, m is the reconstructed image to be obtained, F_u is the undersampled Fourier operator, y is the undersampled k-space measured from scanner, λ is the regularization factor, determined by methods like Tikhonov regularization or L-curve optimization [7], ψ is the sparsifying transform operator and $\|.\|_k$ is the k-norm operator. The unconstrained

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CS problem in (1) can be solved with the data consistency evaluation performed in the image domain and (1) can be re-written as:

$$min_m(\left\|F^{-1}(F_u(m)-y)\right\|_2+\lambda\left\|\psi(m)\right\|_1) \quad (2)$$

where, F^{-1} is the inverse Fourier transform. In the spatial domain, data consistency term is evaluated as opposed to the k-space and is equivalent to (1). ROICS can be derived from (2) where, data consistency term is evaluated in the spatial domain over a ROI. Which is described by a diagonal matrix W of size $(N_s * N_s)$, where N_s is the product of numbers of rows and columns of the image. The use of spatial weighting has also been used elsewhere [8] and this results in (3).

$$min_m(\left\|F^{-1}(F_u(m)-y)*W\right\|_2+\lambda\left\|\psi(m*W)\right\|_1) \quad (3)$$

The ROI relaxed functional now takes the form of (3), where W is the $N_s * N_s$ diagonal matrix which contains a spatial weighting that can be used to specify and evaluate a ROI of the dimensions of the image. ROI mask is included to enhance sparsity in the reconstruction, which implies reduction in the number of data samples required for reconstruction. This is achieved by relaxing the constraint on the data consistency term and he0nce would allow for a sparser solution as the optimization problem is more tolerant towards error from the data consistency term. This would hence result in better reconstructions at higher accelerations compared to conventional CS reconstructions with identical regularization factors and sparsity transforms. Algorithm 1 details the implementation of CS and ROICS.

Algorithm 1 Pseudo-code for CS and ROICS reconstruction (retrospective)

Require: MRA raw data
 step 1. Load raw data
 step 2. Calculate Maximum Intensity Projection
 step 3. Generate variable density sampling pattern
 step 4. Choose undersampling factor and undersampling mask
 step 5. Choose reconstruction type
 if Reconstruction type is CS **then**
  step 6. Apply CS to all frames using (1)
  go to step 8
 else
  step 6. Select ROI
  step 7. Apply ROICS to all frames using (3)
 end if
 step 8. End

III. METHODS

MRA was performed on 4 human volunteers as part of an Ethical Review Board (ERB) approved MRI study. The acquisition consisted of a time of flight multi-slab brain angiogram datasets acquired on 1.5T scanner using a 4 channel head and neck coil and 3D spin echo sequence with TR/TE=25/7 ms, matrix size=256x256 with 79 slices with no CS or PI turned on. ROICS reconstruction was performed on the k-space data obtained from the scanner by retrospectively undersampling acquired k-space. Maximum Intensity Projection (MIP) was determined to the final MRA image and the required acceleration factor was used to generate probability density function (PDF), which controlled the k-space data in variable density sampling pattern using Monte Carlo simulation. This simulation provides required undersampling mask for reconstruction based on incoherence. ROI was drawn by considering the blood vessels required for further analysis, as shown in Fig. 1 where the yellow outline depicts the chosen ROI.

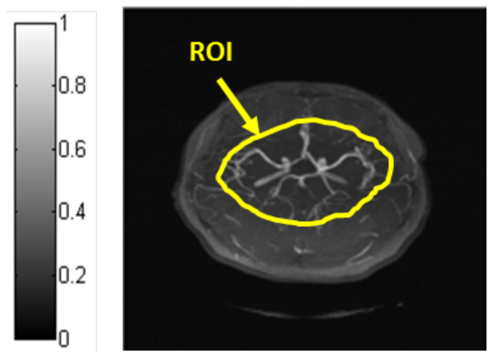

Fig. 1. Selecting ROI on MIP MRA brain image

The ROI selected on The MIP image was used as a mask with binary values, ones (1's) within the ROI and zeros (0's) outside the ROI. This mask was used to implement the ROICS algorithm on angiogram data acquired by applying it on each slice as datailed in Algorithm 1. The non-linear conjugate gradient (NCG) [9] has been well studied and applied among various methods like subspace pursuit, steepest descent method, etc. NCG calculates the direction of the gradient and at each step the length of the step to be taken in the gradient direction is given by a line-search parameter. The stopping criteria for the iterations were 2 fold: 1) the difference of values of the tolerance parameter between successive iterations should be negligible and 2) the value of the tolerance parameter should be smaller than the chosen value. Each slice was reconstructed using ROICS and conventional CS technique.

ROICS and conventional CS technique were implemented on the 4 brain angiogram data sets at undersampling factors of 0.5, 0.33, 0.25, 0.2, 0.125, and 0.1 equivalent to 2x, 3x, 4x, 5x, 8x, and 10x respectively using a variable density sampling with density compensation to compare both techniques. SNR metric was calculated by computing the mean (μ) and standard deviation (σ) within the chosen ROI using (4).

$$SNR=\frac{\mu}{\sigma} \quad (4)$$

where, μ of the image was calculated by selecting only the blood vessel region and σ was calculated from background.

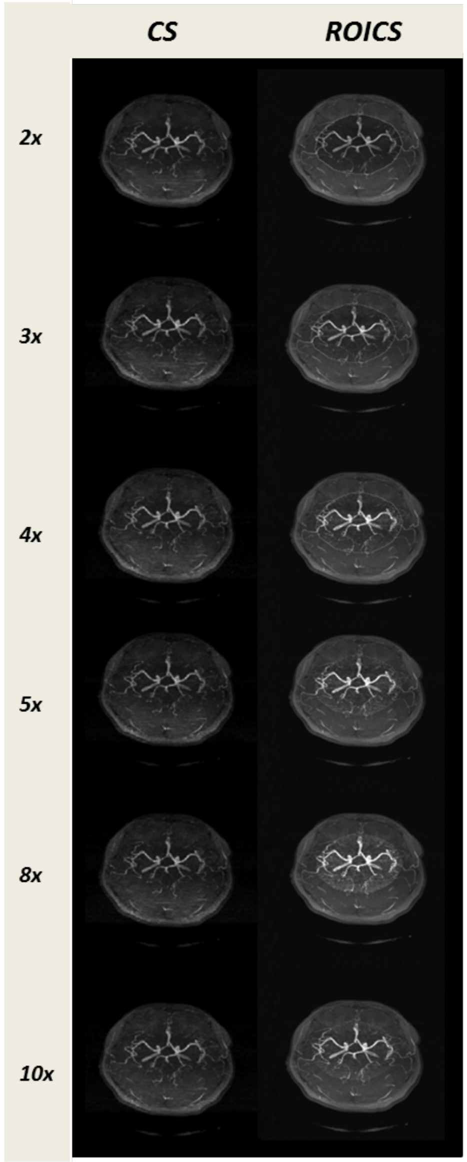

Fig. 2. Comparison of CS and ROICS at chosen acceleration factors

SNR was calculated for both proposed ROICS and conventional CS technique for all data sets at chosen accelerations to plot the average SNR graph.

IV. RESULTS AND DISCUSSION

Fig. 2 depicts the qualitative difference between the conventional CS and novel ROICS on representative data set. It can be observed in Fig. 2 that as the acceleration increases noise in the conventional CS increases more compared to ROICS in the selected ROI.

Fig. 3 validates the superior performance of ROICS observable at acceleration of 3x and above. SNR comparison graph shows that at acceleration factor 2x CS performs as well as ROICS, and as the acceleration increases ROICS performs better than the conventional CS method. This comparable performance of the two techniques at 2x could be attributed to the sufficient k-space coverage in both cases

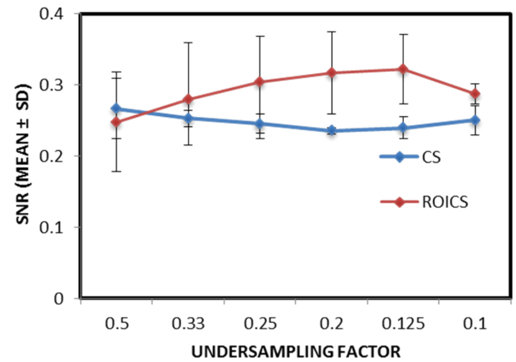

Fig. 3. SNR Comparison of CS and ROICS reconstructed image

for a data type such as the angiogram which is significantly sparse in its native representation.

The μ SNR values of CS decrease with acceleration as is expected but appear to increase at 10x. However, the σ reveal that the improvement is not significant. The ROICS SNR curve similarly has a consistent values of SNR with the chosen values of acceleration when the σ is taken into account. It can be observe in Fig. 3 that SNR for ROICS is increasing with respect to acceleration. However, the σ on these average values depicts a steady SNR trend which is comparatively higher than conventional CS reconstruction rather than an increase in SNR. The angiogram data typically has a background when the MIP is considered which is not relevant for further analysis and selecting the ROI will play a critical role here in the reconstruction since any background inclusion in the ROI selected will be considered as a signal and will not result in better reconstruction.

V. CONCLUSION AND FUTURE WORK

ROICS technique was applied on angiogram data for the first time to demonstrate its utility. Angiograms are sparse in the image domain, hence selection of ROI in the image domain makes data sparse for better reconstruction, where surrounding or background regions are not relatively important for further analysis. ROICS performs better than conventional CS as it limits reconstruction to the ROI and was quantified by evaluating the SNR. Current and future work involves acquiring more angiogram data to perform ROICS and optimizing the k-space trajectory based on ROI shape analysis.

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