Exploiting Similarity in Adjacent Slices for Compressed Sensing MRI

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***Abstract*—Due to fundamental characteristics of MRI that limit scan speedup, sub-sampling techniques such as compressed sensing (CS) have been developed for rapid MRI. Current CS MRI approaches utilize sparsity of the image in the wavelet or other transform domains to speed-up acquisition. Another drawback of MRI is its poor signal-to-noise ratio (SNR), which is proportional to the image slice thickness. In this paper, we use the difference between adjacent slices as the sparse domain for CS MRI. We propose to acquire thick MRI slices and to reconstruct the thin slices from the thick slices' data, utilizing the similarity between adjacent thin slices. The acquisition of thick slices, instead of thin ones, improves the total SNR of the reconstructed image. Experimental results show that the image reconstruction quality of the proposed method outperforms existing CS MRI methods using the same number of measurements.**

I. Introduction

Magnetic Resonance Imaging (MRI) is a reliable imaging method for diagnosis, evaluation and follow-up of brain pathologies, as well as brain activity. However, the acquisition of a routine brain MRI is a relatively slow process. As such, it causes many difficulties, such as patient discomfort during scanning and blurry images due to patient movements during acquisition. Due to the clinical requirement for high resolution MRI, which necessitates acquisition of many data samples at long scanning times, many approaches for MRI acquisition speed-up have been published.

In MRI, data is acquired in the Fourier domain of the image, also known as *k-space*. Compressed sensing [1], [2] techniques have been applied to MRI to significantly reduce the amount of data required for image reconstruction by under-sampling the k-space [3]. CS allows shorter acquisition time by designing specific sub-sampling patterns of the k-space. Reconstruction of the image from the sub-sampled data is then performed by utilizing sparsity of the image in a certain transform domain. The sampling strategy and the reconstruction method are key elements to achieve high quality images from under-sampled k-space data in CS MRI.

Over the past decade, various sampling strategies and reconstruction methods have been developed, utilizing a variety of transform domains for image reconstruction with CS. Some methods utilize the sparsity of MRI in the wavelet domain or other spatial transform domain for various applications of MRI [3], [4], [5]. Others speed-up dynamic MRI by utilizing the similarity of adjacent time frames in dynamic MRI [6], [7], [8], [9], [10].

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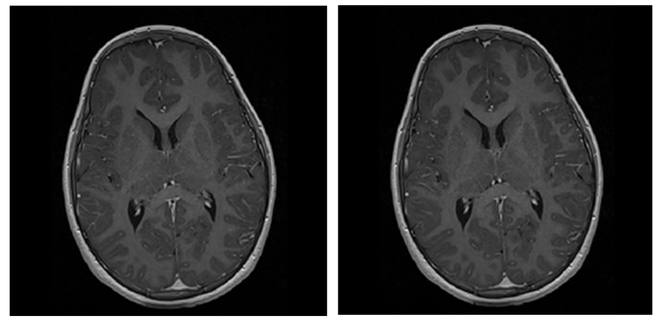

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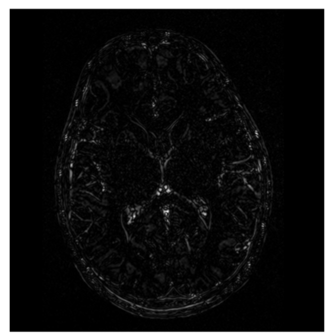

Difference image

Fig. 1: Two adjacent slices taken from 3D MRI scan (top) and the difference image between them (left). Slice thickness is 1mm. It can be seen that the difference image is sparse, thanks to the high similarity between adjacent slices.

In some MRI applications, a 3D image is generated by the acquisition of tens or hundreds of 2D images, coined as *image slices*. In many cases, adjacent 2D slices are very similar due to the slow spatial variations of the scanned object. This phenomenon is emphasized in brain MRI, where 2D thin slices are usually acquired. This similarity between adjacent slices and the sparsity of the difference image are shown in Fig. 1.

In a recently published paper, Pang et al. [4] utilize the similarity between adjacent slices for MRI image reconstruction with undersampled k-space data. They designed a sampling scheme that samples 25% of the k-space in some slices, and 1% of the k-space in other slices. The similarity between adjacent slices is then used to estimate 25% of the k-space of the low-sampled slices. CS based reconstruction is then applied to all slices to obtain the entire image. While novel in its basic idea, their method prioritizes some of the slices over the others by non-uniform sampling over the slices.

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In this paper we aim at utilizing the sparse difference between adjacent slices as a sparse transform domain for the CS-MRI recovery problem. In MRI, the signal-to-noise ratio (SNR) is proportional to the number of protons involved in generating the measured signal. As a result, thick slices provide better SNR than thin ones. Therefore, we simulate the acquisition of under-sampled thick slices, to obtain data with improved SNR over data obtained from thin slices. The reconstruction of the thin slices from the sampled data is then performed, exploiting the similarity between these thin slices. In our approach, no priority is given to certain slices over the others in the sampling process. Experimental results on real MRI data show that the proposed method outperforms, in terms of MSE versus the fully sampled k-space, previous approaches for CS-MRI using the same number of samples.

II. METHOD

A. CS-MRI

CS MRI [3] reconstructs the image using randomly measured k-space samples. The formulation of the basic CS-MRI application is given below. We represent the reconstructed 2D image slice by a complex matrix, $\mathbf{X}$, where $g(\cdot)$ denotes a matrix function that transforms the image domain into a sparse transform domain. Let $f_u(\cdot)$ denote the under-sampled 2D Fourier transform, corresponding to k-space under-sampling. In Lustig et al. work [3], CS MRI reconstruction is obtained by solving the following constrained optimization problem:

$$\min_{\mathbf{X}} \ \|g(\mathbf{X})\|_1 \ \ s.t. \ \ \|f_u(\mathbf{X}) - \mathbf{Y}\|_F < \epsilon \tag{1}$$

where $\mathbf{Y}$ is the measured k-space data from the scanner, and ϵ controls the fidelity of the reconstruction to the measured data.

In brain MRI, the wavelet transform is used in most cases as the sparsifying transform. CS-MRI exhibits high quality reconstruction when sampling only about 15% of the k-space [3]. However, we note that similarity between adjacent slices, which exists in many MRI application, is not taken into account in this CS-MRI reconstruction scheme, which reconstructs a single 2D image image slice, $\mathbf{X}$.

B. Proposed approach

Our approach is based on the acquisition of thick slices, to obtain slices at improved SNR. We utilize similarity between adjacent slices to reconstruct thin slices from the data of the thick acquired slices. As a result, image distortions caused by the summation of the thick measurement region are reduced. Note that while it is practically feasible to acquire thick slices, the results presented in this paper are based on a simulation of thick slices, obtained by averaging adjacent thin slices. Since in our simulations thin slices were acquired with a few repetitions to improve their SNR, noise was added to those slices to simulate the scenario of thin slices acquired with no repetitions, thereby having poor SNR versus thick ones acquired with no repetitions.

In our formulation, two thin adjacent reconstructed slices, $\mathbf{P}_1$ and $\mathbf{P}_2$ are represented by a matrix $\mathbf{X}_C$:

$$\mathbf{X}_C = \begin{bmatrix} \mathbf{P}_1 \\ \mathbf{P}_2 \end{bmatrix} \tag{2}$$

Note that $\mathbf{X}_C$ is not a thick slice but rather the concatenation of two thin ones. In order to simulate a thick slice, we generate a 2D image with a linear combination of $\mathbf{P}_1$ and $\mathbf{P}_2$. We generate two thick slices for each pair of thin slices. Therefore, in our measurement model we under-sample the Fourier transform of the product $\mathbf{A}\mathbf{X}_C$, where the matrix $\mathbf{A}$ is defined as:

$$\mathbf{A} = \begin{bmatrix} a_{11}\mathbf{I} & a_{12}\mathbf{I} \\ a_{21}\mathbf{I} & a_{22}\mathbf{I} \end{bmatrix} \tag{3}$$

In an actual MRI scanner, this weighting is achieved by adjusting the waveform of the RF pulses such that each slice is given a different weight in different acquisitions. Note in order to reconstruct two thin slices with the CS-MRI approach of Lustig et al. [3], one would have to under-sample the k-space of each thin slice individually. In our approach, we actually under-sample the k-space of two thick slices for the same purpose. While we use the same number of k-space samples as Lustig et al., the acquisition of thick slices provides samples with improved SNR, leading to better overall results in terms of MSE as will be further demonstrated in this paper.

By denoting the matrix $\mathbf{B} = [\mathbf{I} \quad -\mathbf{I}]$, the minimization problem for the reconstruction of $\mathbf{X}_C$, in its unconstrained form is:

$$\min_{\mathbf{X}_C} \ \|f_u(\mathbf{X}_C) - \mathbf{Y}\|_2 + \lambda \|\mathbf{B}\mathbf{X}_C\|_1 \tag{4}$$

where $\mathbf{Y}$ denotes the under-sampled measurements of the product $\mathbf{A}\mathbf{X}_C$. The first term in (4) enforces the matching of the solution to the measurements, taken in the Fourier domain in MRI and the second term exploits sparsity of the difference between adjacent slices. In our experiments we solved 4 with the FISTA algorithm [11], where the value of λ was tested for different values in the range of $[10^{-3}, 0.5]$.

III. EXPERIMENTAL RESULTS

We conducted evaluation of our method on contrast-enhanced T1-weighted brain MRI. Image dimensions are $512 \times 512 \times 70$ voxels, and physical dimensions of each voxel are $0.5 \times 0.5 \times 1mm^3$.

Fig. 2 shows an example of original adjacent slices and reconstructed slices with our method, obtained with only 10% of the k-space. The mean square error (MSE) between the reconstruction result and the full-sampled image is defined as:

$$MSE = \frac{1}{MN} \sum_{i=1}^{N} \sum_{j=1}^{M} (\hat{\mathbf{X}}_{Cij} - \mathbf{X}_{Cij})^2 \tag{5}$$

where $\hat{\mathbf{X}}_{Cij}$ and $\mathbf{X}_{Cij}$ are the (i, j)-th pixels of the estimated and the fully sampled thin image slices, respectively, and N and M are the images spatial dimensions. Note that the MSE is computed over two adjacent thin slices, as defined in (2).

To provide a value of reference for the results obtained with our method, we compare the MSE of our method with the MSE for several other approaches for MRI reconstruction:

- CS MRI based on sparsity in the wavelet domain [3]. The CS equation for this approach is given in (1).

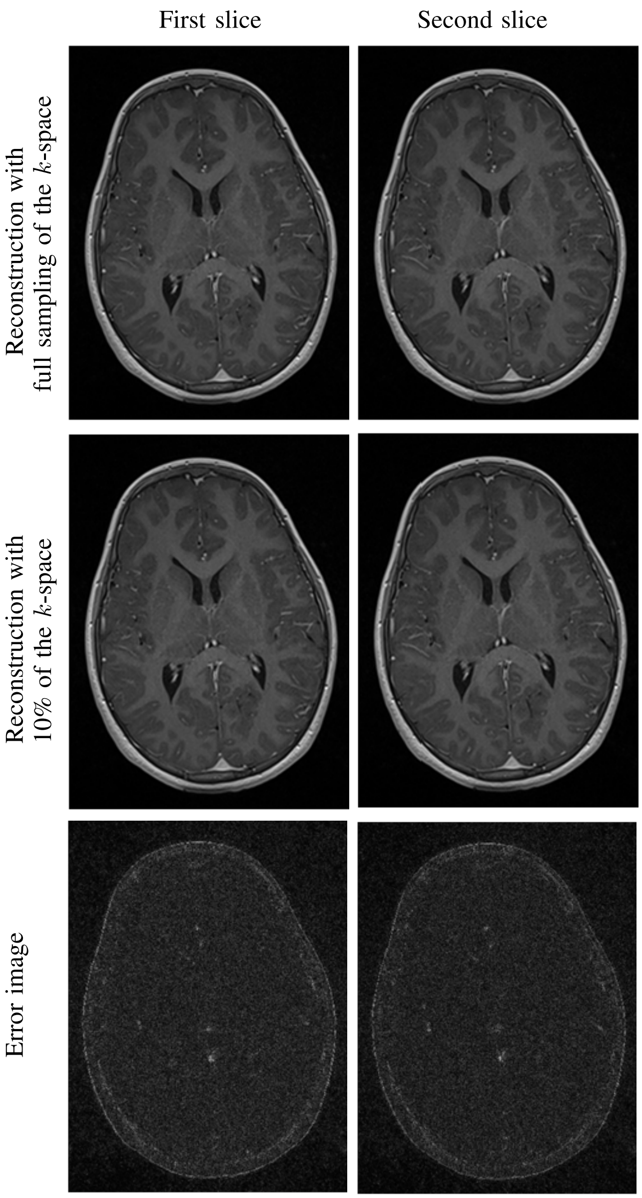

Fig. 2: Example of two adjacent slices (top row). The reconstruction with our method using 10% of the k-space is shown (middle row), together with the error images between the fully sampled and the reconstructed slices (bottom row).

- Interpolating CS (iCS) [4]. This method takes a varying number of samples from each thin slice, and utilizes adjacent slices similarity to interpolate unknown data using samples from adjacent slices.
- Naïve approach of zero-filling the unknown k-space locations after under-sampling the k-space. This method provides the pratical upper bound on the MSE.

In order to perform a fair comparison between the above approaches, we need to take into account that thick slices, simulated in our experiments by averaging of thin slices, have higher SNR than thin ones, which were used for reconstruction by the other approaches. Since thin slices in our data were taken with a number of repetitions to improve SNR, we added noise to those slices, at a level that simulates the case as they were acquired with no repetitions. Fig. 3 shows the comparison results. We examined sampling scenarios of 2% to 23% of the k-space, in each of the slices.

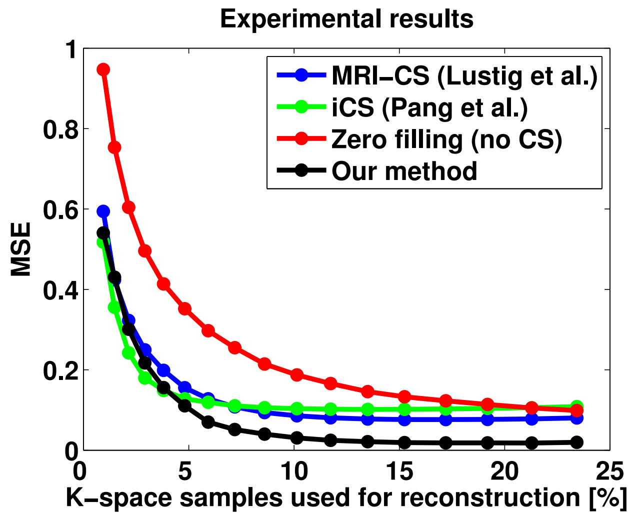

Fig. 3: Experimental results. Each curve represents one of the methods described in the paper. In can be seen that the proposed method (black curve) outperforms other methods for k-space sampling ratio $>5\%$.

The MSE of naïve zero filling reconstruction with no CS is added in order to give the reader the sense of improvement obtained with CS-based methods. The MSE is calculated as the average MSE for the reconstruction of both adjacent slices in all methods used for comparison, to allow fair comparison between the methods.

The simulation shows that our approach achieves better MSE then the other CS approaches, for sampling ratios above 5%. This can be seen in the numerical results presented in Fig. 3, and in a representative example of our method's result shown in Fig. 4. Lower sampling ratios provide insufficient information for adequate recovery, and therefore the results of all CS-based methods for low sampling ratios are very similar.

Parameter sensitivity analysis: Our approach involves four adjustable parameters, needed to be determined as the four constants in the matrix $\mathbf{A}$. While the performance of our method depends on those parameters, it is important to show that reliable results are obtained, regardless of their selection. Therefore, we compute the MSE of our method obtained with various selections of the parameters, obtained with 10% of the k-space. The results are presented in Table I. In our analysis, the parameter values were chosen arbitrarily between 0 and 1, ensuring that the lines of $\mathbf{A}$ are linearly independent.

While in our analysis the parameter selection that provides the best MSE is given in setting #4, other settings provide proper results as well, which indicate the reliability of our method when different parameters sets are used.

TABLE I: Parameter sensitivity analysis. MSE results for various selections of the matrix $\mathbf{A}$.

Setting #	a_{11}	a_{12}	a_{21}	a_{22}	MSE
1	0.5	0.5	0.25	0.75	0.034333
2	0.5	0.5	0.1	0.9	0.034343
3	0.5	0.5	0.4	0.6	0.037234
4	0.5	0.5	0.5	0.75	0.032429
5	0.3	0.7	0.6	0.4	0.049285
6	0.5	0.5	0	0.5	0.04031

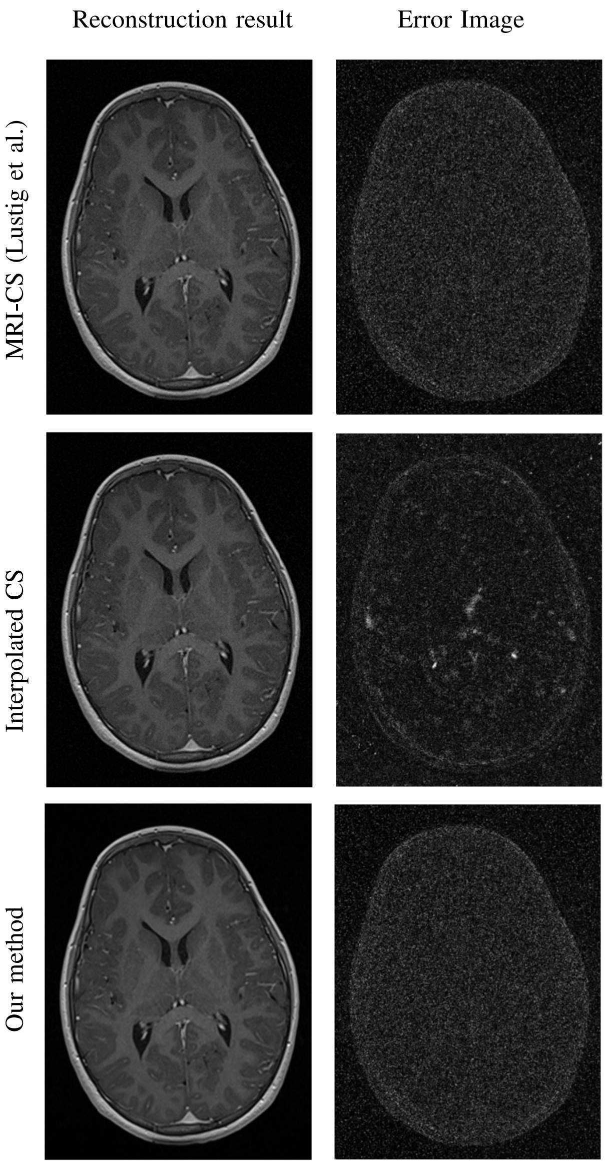

Fig. 4: Example of the results obtained with various CS MRI merhods. Wavelet based reconstruction [3] (top), interpolated CS [4] (middle) and our approach (bottom) are presented. Images were reconstructed form sampling 23% of the k-space.

IV. Discussion and Conclusions

Our approach exhibits high quality reconstruction, and provides reliable reconstruction results using only 5% samples of the k-space. Additionally, our approach outperforms, in terms of MSE, current CS MRI approaches. Reconstruction of images with less than 5% of the k-space provides similar results for all the methods tested in our experiments, due to lack of sufficient amount of data.

For any sampling rates higher than 15%, it can be seen that the basic CS MRI and our approach converge to a constant MSE. However, our approach converges to an MSE which is almost 4 times better than other CS approaches.

Our work provides a way to further reduce the acquisition time for undersampled multi-slice, 2D MRI. In our method, the missing data due to the random sampling of the k-space are reconstructed using the adjacent slices. Using the CS approach in conjunction with the assumption similarity between adjacent slices, the undersampled slices are reconstructed properly.

While our reconstruction method can also be viewed as an extension of Total Variation (TV) reconstruction based methods, the novelty of our approach lies in the acquisition of thick slices, weighted differently, for improved SNR. Future research will focus on exploring variable random sampling patters and extending the proposed method to acquires thicker slices than presented in this paper, for improved SNR.

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