

# HIGH RESOLUTION MRI OF SPINAL CORDS

An Undergraduate Research Scholars Thesis

by

XIANGDONG YU

and

PENG LI

Submitted to Honors and Undergraduate Research  
Texas A&M University  
in partial fulfillment of the requirements for the designation as an

UNDERGRADUATE RESEARCH SCHOLAR

Approved by  
Research Advisor:

Dr. Jim Ji

May 2015

Major: Electrical Engineering

# TABLE OF CONTENTS

	Page
ABSTRACT .....	1
ACKNOWLEDGEMENTS .....	2
NOMENCLATURE.....	3
CHAPTER	
I INTRODUCTION.....	4
Background .....	4
II METHODS .....	7
Image Simulation.....	7
Parallel Imaging and Compressive Sensing .....	8
Six Subsampling Methods .....	8
Reconstruction with Non-linear Conjugate Gradient .....	10
III RESULTS.....	12
IV CONCLUSION .....	16
REFERENCES.....	17

## **ABSTRACT**

High Resolution MRI of Spinal Cords. (May 2015)

Xiangdong Yu  
Department of Electrical and Computer Engineering  
Texas A&M University

Peng Li  
Department of Electrical and Computer Engineering  
Texas A&M University

Research Advisor: Dr. Jim Ji  
Department of Electrical and Computer Engineering

Spinal Cord Injury (SCI) is a common injury in incorrect sitting position, sports and car accidents. Noninvasive imaging methods play a critical role in diagnosing SCI and monitoring the response to therapy. Magnetic Resonance Imaging (MRI), by the virtue of providing excellent soft tissue contrast, is the most promising imaging method for this application. However, spinal cord has a very small cross-section, which requires high-resolution images to visualize. Unfortunately, acquiring high-resolution spinal cord MRI images requires long acquisition time due to the present physical and physiological constraints. Meanwhile, long acquisition time focusing on Spinal Cord is very challenging to achieve since MRI scanner has high requirement on object's stability and human body is moveable. In addition, reconstruction of high-resolution images also demands significant computer power and advanced logical algorithm. In this proposed undergraduate research project, we aim to develop and implement new algorithms that allow high-resolution images to be reconstructed from sparsely sampled, non-uniform k-space data that are acquired from parallel receive arrays, which will enable high-resolution MRI of spinal cords without significantly increase the imaging time.

## **ACKNOWLEDGEMENTS**

We would like to thank Dr. Jim Ji for his tremendous support. His teaching has been paramount to the production of this thesis and our improvement as students and people.

## NOMENCLATURE

SCI	Spinal Cord Injury
MRI	Magnetic Resonance Imaging
DTI	Diffusion Tensor Imaging
fMRI	functional MRI
pMRI	parallel Magnetic Resonance Imaging
CS	Compressed Sensing
FOV	Field of View

# CHAPTER I

## INTRODUCTION

### Background

Spinal Cord is a part of the central nervous system, which is located in the vertebral canal. Spinal Cord is in a long cylindrical shape, and extends from the medulla oblongata in the brainstem. Paired nerves grow out from the sides and distribute to human's arms, legs, body and organs. The entire length of the spinal cord is around 45 cm for an adult man and 43 cm for an adult woman (O'Rahilly, 1983). The width of the spinal cord is varying at different length. It is about 13mm thick in the cervical and lumbar regions and 6.4 mm thick in the thoracic area. Since the spinal cord is surrounded by the cervical vertebra, thoracic vertebra, and lumbar vertebra, it is inaccessible for human research without dissection.

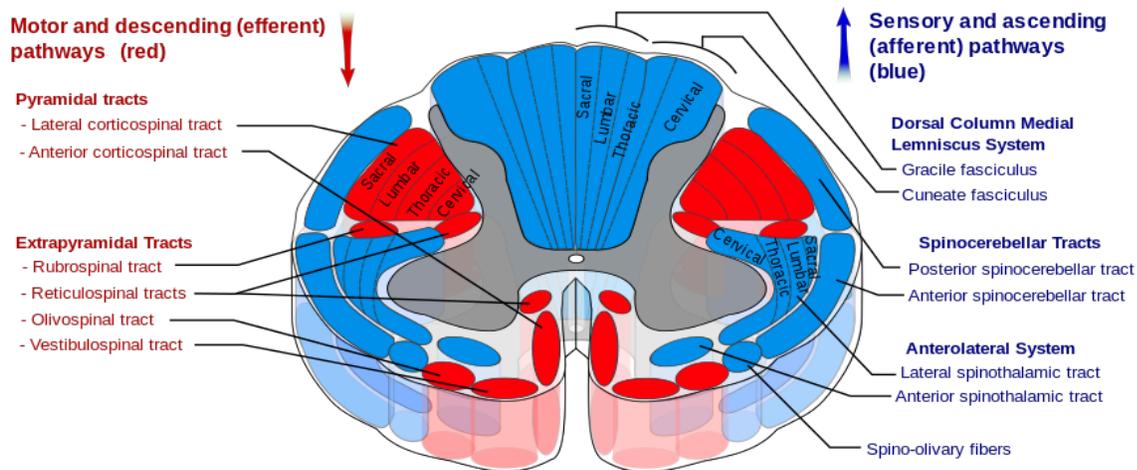


Figure 1 Spinal Cord (Wikipedia contributors, 2014)

Up to now, the previous medical studies have shown that MRI image can help with prognosis and diagnosis of spinal cord injury – hypercalcemia, necrosis, deformation etc. (Bot & Frederik, 2009; Kearney *et al.*, 2013). However, it's still a problem for people to get effective treatment on Spinal Cord Injury. The key is to prevent Spinal Cord Injury through frequent check and adequate prognosis. MRI has been strongly recommended on the previewing of acute SCI because of its brilliant effect for imaging neurological tissues, especially to the sagittal T2 sequence (Falconer *et al.*, 1994). Since the delicate structure of the spinal cord, high resolution MR image is required for the biomedical study. However, present spinal cord MR image has low resolution due to the short acquisition time caused by object movement (Stroman *et al.*, 2014). Therefore, our purpose is to raise the resolution/quality of MR imaging through applying higher magnetic field, diffusion tensor imaging and fast acquisition MRI sequences.

After we reviewed and summarized recent paper, there are couple present unsolved problems that we could choose to focus on, including improving the inhomogeneous magnetic field in the spinal cord, data sampling dimension selection, and choosing phase encoding direction to reduce motion artifacts spreading across the spinal cord (Stroman *et al.*, 2014).

We are trying to analyze and satisfy several things on our research. First of all, in clinical research, we have two key methods on employing Spinal Cord Injury Imaging: Diffusion Tensor Imaging (DTI) and functional MRI (fMRI) and four different strategies to focus on Spinal Cord Injury, including investigations of cervical spondylotic myelopathy (CSM), spinal cord injury (SCI), pain and multiple-sclerosis (MS) (Wheeler-Kingshott *et al.*, 2014). Apparently, we are working on achieving high resolution image on Spinal Cord Injury. Functional MRI can detect

changes according to tasks or sensory stimuli based on producing quick and repeated anatomical images over time. So far, fMRI has been well developed in brain function and we want to work on fMRI adaptation from brain fMRI. Additionally, diffusion tensor imaging is an effective way to detecting pathological changes since DTI works on the interaction between protons in water and their surrounding which adjust to relaxation time. Similarly to the fMRI method, even though encoding diffusion sensitivity and acquiring diffusion-weighted imaging have widely applied in brain, it still needs to be explored in utilizing on spinal cord (Stroman *et al.*, 2014). In one of recent research, it became an impressive success on using DIT measurement with iFOV, which is relatively small rectangular FOV since spinal cord has a small-diameter cross section, to get high-resolution pediatric spinal cord (Barakat, Mohamed *et al.*, 2012).

This is a quite frontier topic to studying MRI scanner on Spinal Cord Injury and there are no former students working on this project before. However, the research group followed by our research adviser has done several experiments before and expects to make a big progress on improving the image resolution. We won't participate on doing the spinal cord physical experiment. Instead, we will try to simulate on the advanced language environment, like C++ or Matlab to achieve parallel imaging method and compressive sensor function adopting in different parameters to get random data sets to decrease long acquisition time effectively according to previous experiments.

## CHAPTER II

### METHODS

#### Imaging Simulation

Computer image simulation can help to analyze alternative parameters working on image quality. The simulation of brain 2d phantom image and k-space data has been implemented on Matlab by Dr. Ji and his colleagues (Ji *et al.*, 2008). They use a set of functions to change and call different design parameters:

```
function varargout = brain2D(datatype, Nsiz, Nsets , txy, theta, varargin).
```

Datatype decided we want to get “i”(real image) or “f” (Fourier data, k-space); the size of matrix for each image slice is determined by Nsiz; Nsets is defined by how many slices for the phantom dataset. Txy and theta decided the translation and rotation for each image slice. One of data simulation result set, reconstructing a 256\*256 with 10 pieces brain phantom, from k-space data with 1 unit translation along x, and y direction and 10 degree rotation between two neighboring image frame, is as follow:

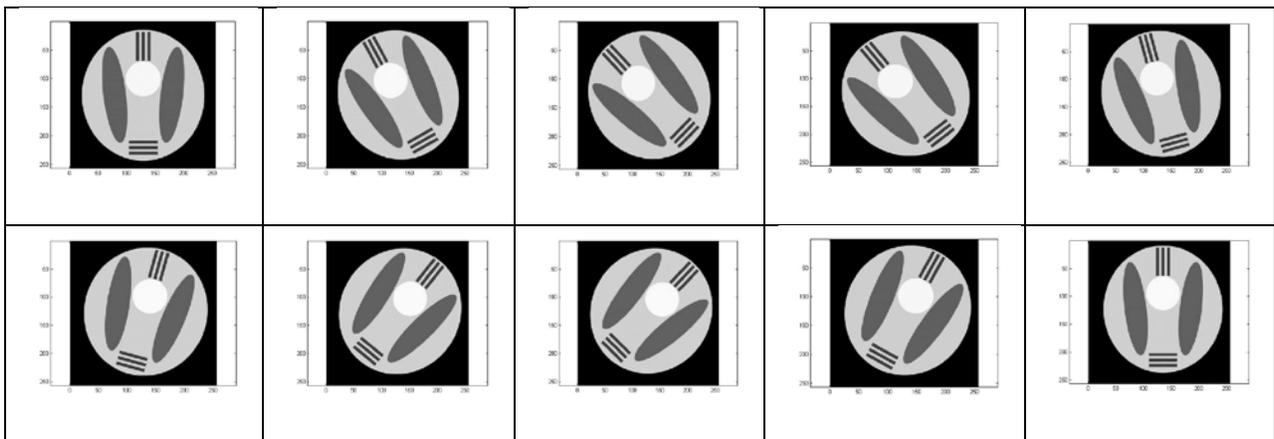


Figure 2. 10 Sets of Different Angle Image Rotation (Ji et al., 2008 )

From the figure2 shown above, each simulation image was consisted of an upper-left rectangle, an upper-center rectangle, an upper-right rectangle, a right ellipse, a left ellipse, the first lower rectangle, the second lower rectangle, the third lower rectangle, the big ellipse containing all the other 8 components inside. Those 9 sets of compartments have their own temporal intensity. We are in process of changing the shapes of various compartments to achieve the simulation of spinal cord tracts.

### **Parallel Imaging and Compressive Sensing**

pMRI method is one way to reduce the scanning time by setting multiple channel receiver (coil array) in parallel. Here, k-space data will be acquired by multiple receive-channels simultaneously instead of using one coil. Meanwhile, CS is a complementary fast image method by reducing the amount of required k-space data. Under the theory of the compressive sensing, the image can be reconstructed even if the sampled rate of original k-space is lower than the Nyquist criterion (Ji *et al.*, 2008). Two conditions need to be satisfied before using the compressed sensing: sparsity and incoherence. The former requires signal to be sparse in a transformed domain. The later requires incoherence between aliasing artifacts caused by under sampling and sparse transform. pMRI and CS method have been integrated for improved fast imaging, which also requires the k-space to be subsampled.

### **Six Subsampling Methods**

MRI image data is sampled on 2D Fourier transform domain, which is the spatial frequency domain. In the study, fully sampled k-space data is firstly acquired. Subsampled data is simulated by decimating the original k-space data. The reduction is performed along the PE

direction. In practice, reduced PEs leads to reduced data acquisition time. Six subsampling schemes have been tested in our study. The six subsampling schemes are:

(a) Uniformly sampling.

(b) Central k-space sampling.

(c) Uniformly outer k-space plus a fully central k-space sampling.

(d) Non-uniformly sampled outer k-space plus a fully central k-space sampling. Sampling density decreases linearly as it moves away from the center k-space.

(e) Randomized subsampling. One line is selected randomly within each block, which consists of R adjacent PE lines.

(f) Randomized outer k-space plus a fully central k-space sampling.

For each subsampling scheme, 4 different reduction factors (5, 4, 3, and 2) are used. The reduction factor is calculated by:

$$R = \frac{\text{number of fully sampled PE lines}}{\text{number of sub-sampled PE lines}} \quad (1)$$

Figure 3 shows the six sampling schemes at R = 3.

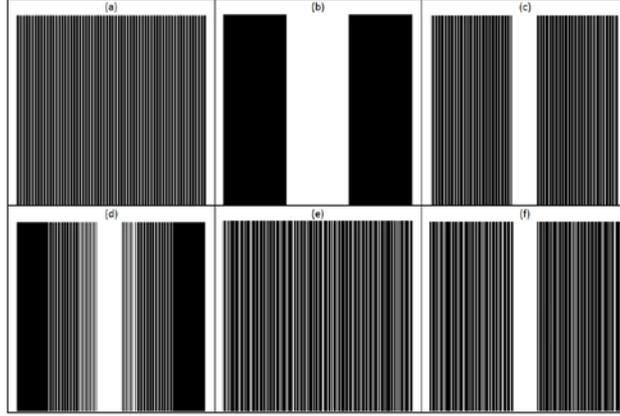


Figure 3. Illustrations of the six sampling schemes (at reduction factor of 3). (a) Uniform; (b) Central k-space; (c) Uniform outer k-space plus central k-space; (d) Non-uniform k-space plus central k-space; (e) Random; (f) Random outer k-space plus central k-space.

### Reconstruction with Non-linear Conjugate Gradient

In pMRI method, the image is reconstructed by:

$$S = W\rho \quad (2)$$

where  $S$  is the data vector that contains the multichannel k-space data,  $W$  is the encoding matrix incorporating channel sensitivity and Fourier transform, and  $\rho$  is the image vector to be reconstructed.

In our study, CS is used as a regularization which includes a L1 term and a total variation term for solving (2) by minimizing

$$\|W\rho - S\|_2^2 + \lambda_1 \|F\rho\|_1 + \lambda_2 TV(\rho) \quad (3)$$

where  $\lambda_1$  and  $\lambda_2$  are two regularization parameters,  $\|F\rho\|_1$  is for the L-1 norm term and  $TV(\rho)$  stands for the total variation.

A nonlinear conjugate gradients algorithm with fast backtracking method is used to solve (3).

More details on the algorithm and selecting the values of  $\lambda_1$  and  $\lambda_2$  can be found in the papers

(Lustig *et al.*, 2007, Ji *et al.*, 2008) and its references. All data processing and algorithms are implemented in Matlab.

Reconstructed images are evaluated by visual inspection and by quantitative comparison based on a normalized mean square error (nmse):

$$nmse = \frac{\|\rho_o - \rho\|^2}{\|\rho_o\|^2} \quad (4)$$

where  $\rho_o$  is a reference image from fully sampled k-space data.

## CHAPTER III

### RESULTS

The primary purpose for image simulation is taking advantage of different image processing methods on virtual image before sampling real data. The progress on parallel imaging and compressive sensing is much faster and satisfied. The method was put directly on the SCI data.

To test the proposed method, a set of transverse spinal MRI images was acquired from an injured dog on a 3T whole-body scanner. A fast spin-echo sequence was used with the following parameters are: TR=4200 ms, TE= 94 ms, FOV=60 mm, SL = 3 mm, ETL = 22, and data matrix:  $256 \times 256$ . Therefore, the in-plane resolution is 0.23 mm in both directions. A 4-channel k-space dataset were simulated by modulate the image with the coil-sensitivities calculated using the quasi-static simulation based on Biot-Savart law (Ji *et al.*, 2007).

Figure 4 shows the high-resolution reference image reconstructed from the fully sampled data.

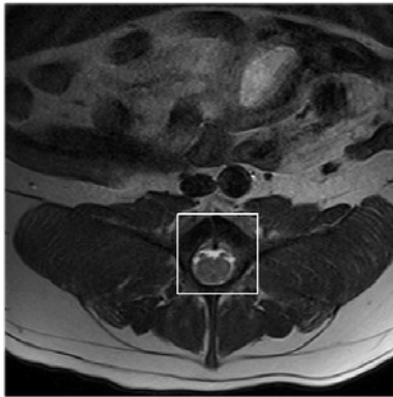


Figure 4. Reference image

The k-space data were then decimated according to the 6 different schemes with different reduction factor R. For (c), (d), and (f), the number of central PE lines is 32 or half of the sub-

sampled PE lines, whichever is smaller. For each dataset, an image is reconstructed using the method described in the previous section. For visualization, zoom-in images corresponding to the region highlighted in Figure 4 are shown in Figure 5. For comparison, the region from the reference image is shown on top of all other 6 reconstructions. As shown, (a) and (e) are mostly close to the high-resolution reference.

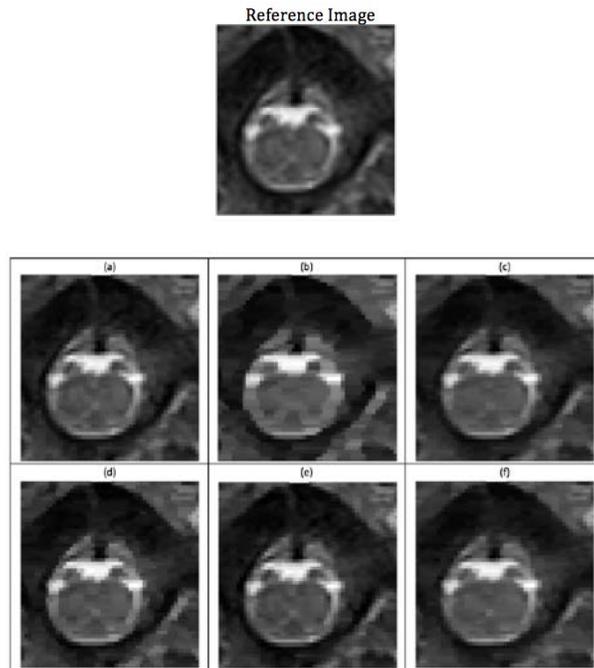


Figure 5. Spinal cord zoomed in with six subsampling schemes at reduction factor of 3.

To further assess the reconstruction quality, the error images, which represent the difference between the reconstructed images and the reference image, are shown in Figure 6. As can be observed, (a) contains the least structured artifact and is preferred.

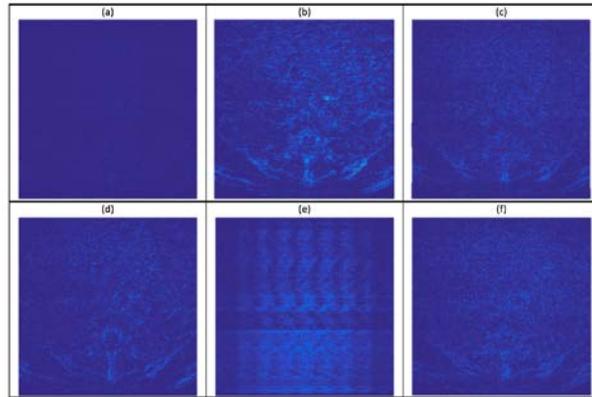


Figure 6. Mean square error with six subsampling schemes at reduction factor of 3. The nmse is (a) 0.017; (b) 0.070; (c) 0.047; (d) 0.044 (e) 0.069 (f) 0.052.

Figure 6 presents a quantitative comparison between reconstructions from different sampling schemes at different reduction factors. Note that lower nmse represents higher reconstruction quality; and higher R represents faster data acquisition. Image reconstruction time on the computer is independent to the data acquisition time on the scanner.

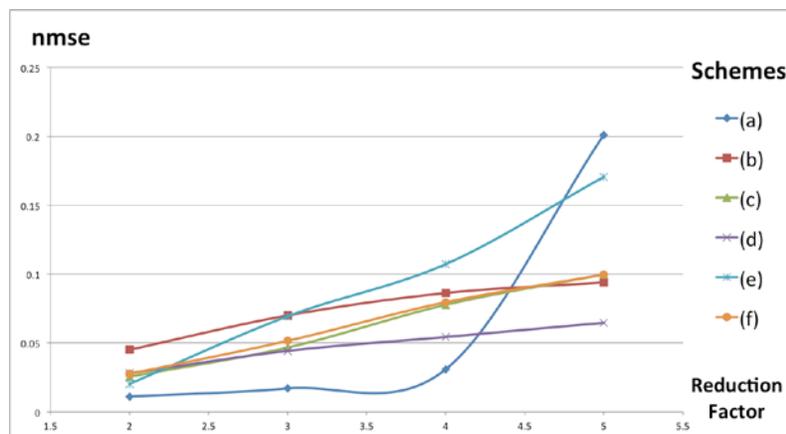


Figure 7. Normalized mean square error (nmse) v.s. reduction factor (R)

The results in Figure 7 show that sampling scheme (a), i.e., uniform sampling, leads to highest quality when  $R \leq 4$ , which is the number of parallel channels. At  $R=5$ , (c) and (f), which includes a fully sampled central k-space portion, provide highest quality. This is expected as with  $R < 4$  the system is over determined even with uniform sampling. In that case, the CS is serving as regularization for parallel imaging and no random sampling is required.

## **CHAPTER IV**

### **CONCLUSION**

In this paper, we studied using compressive sensing parallel imaging for acquiring high-resolution MRI image of the spinal cord. Six different commonly used sampling schemes were studied and compared. Qualitative and quantitative comparisons from simulations show that the uniform subsampling leads to highest reconstruction quality when the reduction factor is less than the number of parallel channels. However, when reduction factor is above the number of channels, a combination of central k-space data and random sampling in other part seems to provide the highest quality.

Future work will include validations with real parallel imaging data, more efficient algorithms for high-resolution MRI, and further explore the limit of achievable resolution on the clinical scanner.

## REFERENCES

- Wikipedia contributors. "Spinal cord." *Wikipedia, The Free Encyclopedia*. Wikipedia, The Free Encyclopedia, 18 Aug. 2014. Web. 28 Aug. 2014.
- O'Rahilly, Ronan, and Fabiola Müller. "Chapter 41: The Spinal Cord and Meninges." *Basic Human Anatomy: A Regional Study of Human Structure*. Philadelphia: Saunders, 1983. N. pag. Print.
- Bot, Joseph Cj., and Frederik Barkhof. "Spinal-Cord MRI in Multiple Sclerosis: Conventional and Nonconventional MR Techniques." *Neuroimaging Clinics of North America* 19.1 (2009): 81-99. Web.
- Kearney, H., K.a. Miszkiel, M.c. Yiannakas, O. Ciccarelli, and D.h. Miller. "A Pilot MRI Study of White and Grey Matter Involvement by Multiple Sclerosis Spinal Cord Lesions." *Multiple Sclerosis and Related Disorders* 2.2 (2013): 103-08. Web.
- Falconer, James C., Ponnada A. Narayana, Meena B. Bhattacharjee, and Shi-J. Liu. "Quantitative MRI of Spinal Cord Injury in a Rat Model." *Magnetic Resonance in Medicine* 32.4 (1994): 484-91. Web.
- Stroman, P.w., C. Wheeler-Kingshott, M. Bacon, J.m. Schwab, R. Bosma, J. Brooks, D. Cadotte, T. Carlstedt, O. Ciccarelli, J. Cohen-Adad, A. Curt, N. Evangelou, M.g. Fehlings, M. Filippi, B.j. Kelley, S. Kollias, A. Mackay, C.a. Porro, S. Smith, S.m. Strittmatter, P. Summers, and I. Tracey. "The Current State-of-the-art of Spinal Cord Imaging: Methods." *NeuroImage* 84 (2014): 1070-081. Web.
- C.A. Wheeler-Kingshott, P.W. Stroman, J.M. Schwab, M. Bacon, R. Bosma, J. Brooks, D.W. Cadotte, T. Carlstedt, O. Ciccarelli, J. Cohen- Adad, A. Curt, N. Evangelou, M.G. Fehlings, M. Fillippi, B.J. Kelley, S. Kollias, A. Mackay, C.A. Porro, S. Smith, S.M. Strittmatter, P. Summers, A.J. Thompson, I. Tracey. "The Current state-of-the-art of spinal cord imaging: Applications." *NeuroImage* 84 (2014): 1082-1093. Web.
- Barakat, N., F. B. Mohamed, L. N. Hunter, P. Shah, S. H. Faro, A. F. Samdani, J. Finsterbusch, R. Betz, J. Gaughan and M. J. Mulcahey (2012). "Diffusion tensor imaging of the normal pediatric spinal cord using an inner field of view echo-planar imaging sequence." *AJNR Am J Neuroradiol* 33(6): 1127-1133.
- Lustig M, Donoho DL and Pauly JM. Sparse MRI: The application of compressed sensing for rapid MR imaging. *Magnetic Resonance in Medicine*, 2007; 58(6):1182-1195.
- J. Ji and Y. Jiraraksopakun, "Model-Based Simulation of Dynamic Magnetic Resonance Imaging Signals," *Biomed. Sig. Proc. Contrl.* V. 3(4), pp. 305-311, 2008.
- J. Ji, C. Zhao (\*), and T. Lang (\*), "Compressed Sensing Parallel Magnetic Resonance Imaging," *Proc. 30th IEEE-EMBS*, pp. 1671-1674, Vancouver, August, 2008

Ji, Jim X., Jong Bum Son, and Swati D. Rane. "PULSAR: A Matlab Toolbox for Parallel Magnetic Resonance Imaging Using Array Coils and Multiple Channel Receivers." *Concepts in Magnetic Resonance Part B: Magnetic Resonance Engineering* 31B.1 (2007): 24-36. Web.