An Efficient Sparse Sampling Approach to Magnetic Resonance Imaging

Arvinder Kaur[1]
[1]Student
[1]Department of Image Processing
[1]Panjab University, Chandigarh, India

Abstract— It is well known that a nuclear resonance magnetic field is used in capturing a MRI image in medical field. When one goes for MRI, he is kept under the nuclear field scanning (approximately under 64 MHz range) for a wide span of time. This instead of helping adds harm to patient's health. A new technique sparse sampling or compressive sensing has come into the picture, by using which number of measurements or samples taken can be reduced to a very little number than that were used initially and thus number of radiations bombarded to patient can also be reduced to a great extent. The image we get is little tolerated on PSNR value but has an observable quality. This appear focuses on reducing the recovery timings of MRI image by fitting compressive sensing to MR imaging.

Key words: MRI, Recovery, Sparsity, Compressed sensing (CS)

I. INTRODUCTION

Compressed Sensing (CS) or sparse sampling is a new study that has attracted considerable research interest in the community of signal processing [1]. In today's world all Analog to Digital Converting devices are based on the popular Shannon Nyquist theorem of reconstruction which needs a double value of sampling rate than the frequency range of signal. A number of signal processing applications are based on this theorem, for example radar, astronomy, medical imaging, video processing and speech processing etc. But as the amount of data transferring from here to there is increasing day by day due to advancement of technology, a problem with the bandwidth required has been raised. Compressed Sensing or sparse sampling is a new technique that was introduced by the will to sample wideband signals at a rate which is much lesser than the Nyquist rate. This technique retains the important information of the signal. Thus we are available with a method that gives us almost the same signal in a quite less time than the traditional methods used for acquiring and reconstruction of a signal.

II. PRINCIPLES OF MRI

The protons present water molecules in human body are responsible for generation of an MRI signal [1,6]. These protons are polarized by an effective magnetic field B0 and as an effect a net magnetic moment is produced in the direction of magnetic field. At this point, to this net magnetic moment a radio frequency excitation field B1 is applied and another magnetic moment component is produced in transverse direction to the initially applied magnetic field. The characteristic frequency of the process is given by

$\nu = (k/2\pi)\ B0$

k is a constant [1]. Generally clinical MRI equipments are based on a frequency of about 64 MHz [1,4]. The transverse component m(n) generated produces a signal that is given to the receiver coil for detection. A number of physical properties like density, volume etc of tissue are represented by this transverse component. The image what is desired to be taken is this transverse component m(n). it is explained in Figure 3.

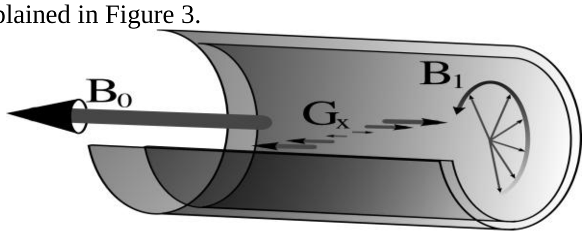


Fig. 1: Magnetic fields used during an MRI scan. B0 creates a net magnetic moment at a characteristic frequency ν. The radio frequency magnetic field B1 is used to exciting the magnetic moment produced. The gradient fields are used for coding in spatial domain [1].

III. THE SPARSITY OF MR IMAGES

It is well known that natural images can be compressed with little loss of information [9]. The commonly known World Wide Web uses this aspect million of times in a week [2]. Although traditionally compression has been avoided in applications related with medical field [2], yet medical images are just as compressible as other images [9].

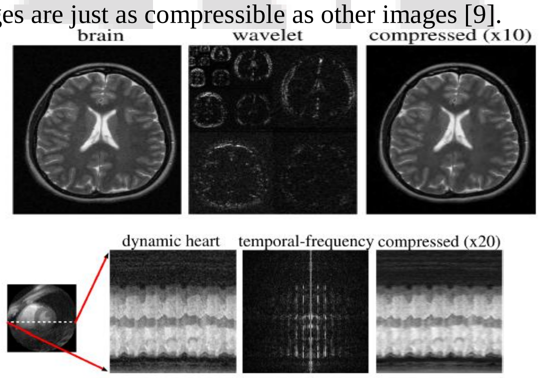


Fig. 2: Sparsity of MR images in another transform. Fully sampled image of brain is mapped into wavelet sparse transform domain (during which many highest coefficients are retained while all others are set to zero) and then the inverse transform is imposed to recover the original image [1].

In CS technique first a stage of sparse transform is generated in any domain such as Wavelet, Fourier, Cosine etc. then a random measurement matrix is generated, and then sparse vector is encoded by ignoring the smaller coefficients and estimating the most significant one. The Discrete wavelet Transform is the sparse transform that lies at the heart of JPEG-200-, while the cosine transform is used with JPEG.

IV. NATURAL FIT BETWEEN CS AND MRI

MR acquisition has a coded nature and its transform Sparsity makes implementation of sparse sampling possible in MRI [3].

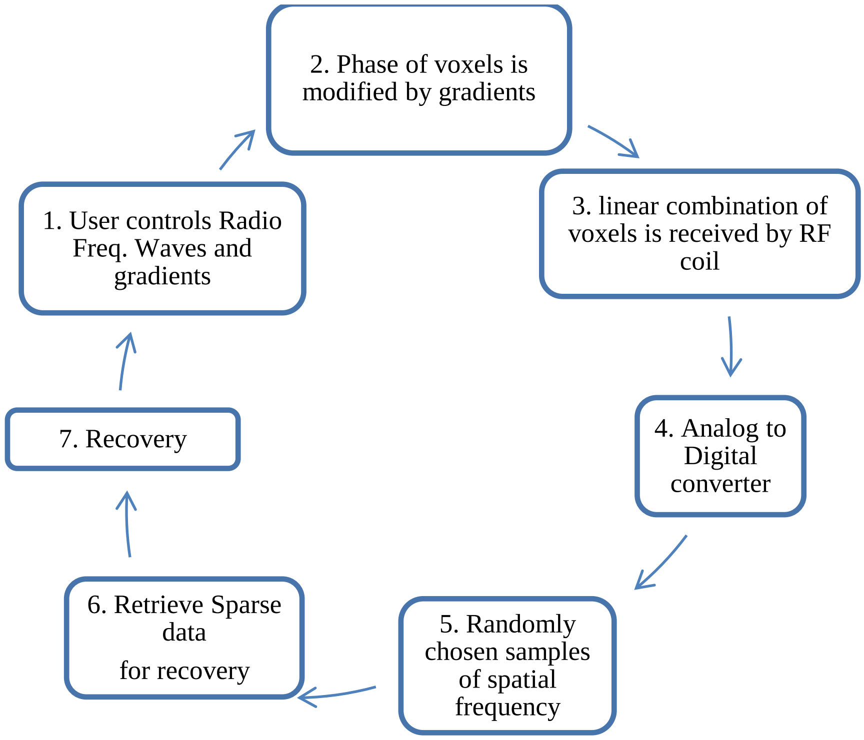


Fig. 3: MRI as a compressed sensing system

Generally three conditions are necessary for CS to take place in MRI: The medical image we want to reconstruct must be compressible by known transform coding. Secondly, the randomly chosen coefficients must be alike, i.e. they should be incoherent to each other [1-2]. The image must be reconstructed by using non linear equipments [1-2].

V. IMPLEMENTING CS ON MRI

In this paper a standard brain MRI images is taken used. The image is of standard size of 256*256. The compressed sensing recovery algorithm is implemented on this image. The test MRI image is shown in figure 4.

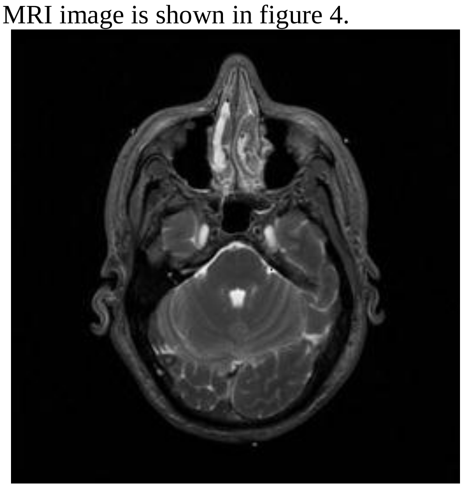
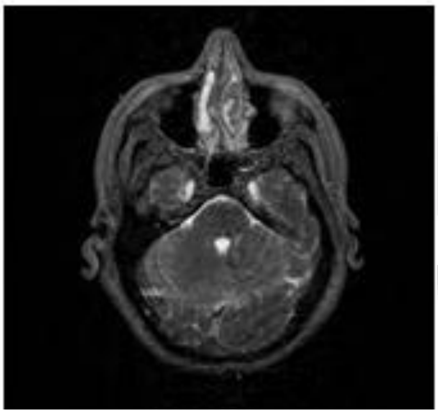
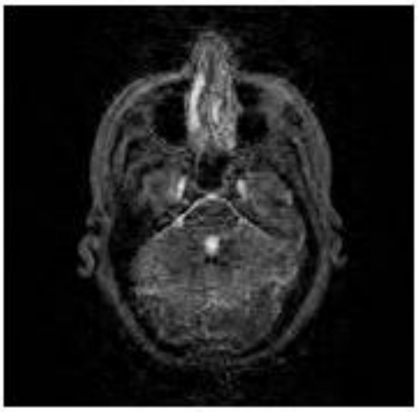


Fig. 4: MRI of Brain

The Sparsity is generated by using discrete wavelet transform. Then as stated in the mechanism, a randomly chosen measurement matrix is formed which is the key task of reconstruction process. Numbers of measurements or the sampling rate are varied to check the observable quality. In fig 5 the reconstructed images for MRI image is shown.



(a)



(b)

Fig. 5: (a) MRI image of Brain Reconstructed using Compressed Sensing, No of measurements =150 (b) Reconstructed with No of measurements =90

Table 1 represents a comparison of reconstruction timings for a traditional method of image reconstruction called Back Propagation reconstruction and compressive sensing reconstruction technique.

No of measurements	Reconstruction time (s)	
	Back Propagation MRI Recovery	**CS MRI Recovery**
90	2.7209	0.5937
150	6.0478	4.0836

Table 1: Comparison of Reconstruction time for MRI image with Back Propagation and CS algorithms

From the results it has been proved that compressed sensing reconstruction method provides a faster recovery than the traditional Back Propagation reconstruction.

VI. CONCLUSION

The compressed sensing algorithm is implemented on brain MRI. Simulation results show that a lesser scanning or reconstruction time is achieved as compared to traditional processes of image reconstruction. By implementing compressive sensing in MRI scan, the effect of radiations given to patient is decreased up to an extent as the number of samples to be taken is decreased which in turn decreases the scanning time thus making it beneficial for the patient's health.

REFERENCES

[1] David L. Donoho Member, IEEE, Michael Lustig, , Juan M. Santos and John M. Pauly, "Compressed Sensing MRI".
[2] Donoho DL. Compressed sensing. IEEE Trans INF Theory 2006; 52: 1289–306.
[3] Michael Elad, Mario A.T. Figueiredo, and Yi Ma," On the Role of Sparse and Redundant Representations in Image Processing"
[4] Sai Prasad Ravishankar , and Yoram Bresler, "Learning Sparsifying Transforms" IEEE Transactions on signal Processing, vol. 61, no. 5, march 1, 2013
[5] Sparse and Redundant Representations: From theory to applications in signal and image processing by Michael Elad.
[6] Laura B. Montefusco, Damiana Lazzaro, Serena Papi, and Carla Guerrini "A Fast Compressed Sensing Approach to 3D MR Image Reconstruction " 1064 IEEE Transactions on medical imaging, Vol. 30, No. 5, May 2011
[7] Donoho DL, Elad M, Temlyakov VN. Stable recovery of sparse over complete representations in the presence of noise. IEEE Trans Inf Theory 2006; 52:6–18.
[8] Donoho DL, Huo X. Uncertainty principles and ideal atomic decomposition. IEEE Trans INF Theory 2001; 47:2845–62.
[9] D. Donoho, "For most large underdetermined systems of linear equations, the minimal `1 solution is also the sparsest solution," Comm. Pure Appl. Math., vol. 59, pp. 797–829, June 2006.
[10] Hansen, "Generalized sampling and infinite dimensional compressed sensing," Feb. 2011, Preprint.
[11] D.L. Donoho, M.R. Duncan, Digital curve let transform: strategy, impel- mentation and experiments, in: Proceedings of the SPIE 4056 (2000) 12–29.
[12] Aurélien Bourquard and Michael Unser, "Binary Compressed Imaging" 1042 IEEE Transactions on image processing, Vol. 22, No. 3, March 2013
[13] Junzhou Huang , Shaoting Zhang, Dimitris Metaxas "Efficient MR image reconstruction for compressed MR imaging" Department of Computer Science, 110 Frelinghuysen Road Piscataway, NJ 08854-8019, USA.
[14] Xue Bi a,b,n, Xiang-dong Chen a, YuZhang c, BinLiu "Image compressed sensing based on wavelet transform in contour let domain" implementation and experiments, in: Proceedings of the SPIE 4056 (2000) 12–29