Research Article Impact Factor: 4.226 ISSN: 2319-507X
Ameera Mulla Muzawar, IJPRET, 2016; Volume 4 (9): 679-684 IJPRET

INTERNATIONAL JOURNAL OF PURE AND APPLIED RESEARCH IN ENGINEERING AND TECHNOLOGY

A PATH FOR HORIZING YOUR INNOVATIVE WORK

IMAGE RECONSTRUCTION USING COMPRESSED SENSING

AMEERA MULLA MUZAWAR, DR. NITESH GUINDE

Dept. Electronics Communication & Instrumentation, Farmagudi, Goa.

Accepted Date: 15/03/2016; Published Date: 01/05/2016

Abstract- The Shannon sampling theorem specifies that to avoid losing information when capturing a signal, one must sample at least two times faster than the signal bandwidth. In many applications, including digital image and video cameras, the Nyquist rate is so high that too many samples result, making compression a necessity prior to storage or transmission. A new method to acquire and represent compressible signals at a rate significantly below the Nyquist rate. This method called Compressive sensing that employs non-adaptive linear projections that preserve the arrangement of the signal; the signal is then reconstructed from these projections using an optimization process. Acquiring Medical image is a most important medical technique. This process is time consuming and can take several minutes to obtain one image. The aim of this paper is to compare the MRI images into different transform domains with orthogonal matching pursuit as reconstruction algorithm.

Keywords: Compressive Sensing, Sparsity, Measurement matrix, Reconstruction Algorithm.

PAPER-QR CODE

Corresponding Author: MS. PHADTE SNEHA KISAN

Access Online On:

www.ijpret.com

How to Cite This Article:

Ameera Mulla Muzawar, IJPRET, 2016; Volume 4 (9): 679-684

INTRODUCTION

Medical imagery is crucial for diagnosis and treatment. Many imaging techniques are currently being implemented in hospitals. Magnetic Resonance Imaging(MRI) is medical imaging technique used in radiology to image the anatomy and the physiological processes of the body in both health and disease. It has an edge over other techniques; it differentiates between all kinds of tissues, which make it extremely useful for brain and cancer. Since MRI does not use any ionizing radiation, its use is generally favoured in preference to CT when either modality could yield the same information. The methods based on reducing the total measurements mostly circle around the design of exploiting the redundancy of medical images. Compressive Sensing in MRI comes under this class.

1) *COMPRESSIVE SENSING*

Compressive Sensing [1] is a new approach where a signal that is sparse in a known transform domain can be acquired with much fewer samples than usually required by the dimensions of this domain. The only condition is that the sampling process is incoherent with the transform that achieves the sparse representation and sparse means that most weighting coefficients of the signal representation in the transform domain are zero.

Consider a real-valued, finite-length, one-dimensional, discrete-time signal x, which can be viewed as an *N* × 1 column vector in R^N with elements x [*n*],*n* = 1, 2, . . . , *N*. (We treat an image or higher-dimensional data by vectorizing it into a long one-dimensional vector.) Any signal in R^N can be represented in terms of a basis of *N* × 1 vectors$\{\psi i\}_{i=1}^{N}$. For simplicity, assume that the basis is orthonormal. Using the *N* × *N basis* matrix ψ = [$\psi_1 \psi_2 \ldots \ldots \psi_N$] with the vectors {$\psi_i$} as columns, a signal x can be expressed as $\mathrm{x} = \sum_{i=1}^{N} s_i \, \psi_i$ or x = ψs.

Where s is the *N* × 1 column vector of weighting coefficients s_i=(x,ψ_i) = ψ_i^T x and ·*T* denotes transposition. Clearly, x and s are equivalent representations of the signal, with x in the time or space domain and s in the transform domain[4]. The signal x is *K*-sparse [6] if it is a linear combination of only *K* basis vectors; that is, only *K* of the s_i coefficients are nonzero and *(N − K)* are zero. The case of interest is when *K* << *N*. The signal x is compressible if the representation (1) has just a few large coefficients and many small coefficients.

Compressive sensing addresses these inefficiencies by directly acquiring a compressed signal representation without going through the intermediate stage of acquiring *N* samples. Consider a general linear measurement process that computes *M* < *N* inner products between x and a collection of vectors $\{\varphi_j\}_{j=1}^{M}$ as in y_j = (x, *φj*). Arrange the measurements y_j in an *M* × 1 vector **y** and the measurement vectors φ_j^T as rows in an *M* × *N* matrix. Then, by substituting ψ from (1), **y** can be written as **y** = φ x = $\varphi\psi$s= As**.**

Where $A=\varphi\psi$ is an $M \times N$ matrix. The measurement process is not adaptive, meaning that *A* is fixed and does not depend on the signal x. The problem consists of designing a) a stable measurement matrix *A* such that the salient information in any *K*-sparse or compressible signal is not damaged by the dimensionality reduction from x $\in R^N$ to **y** $\in R^M$ and b) a reconstruction algorithm to recover x from only $M \approx K$ measurements **y.**

2) *DESIGNING A STABLE MEASUREMENT MATRIX*

The measurement matrix must allow the reconstruction of the length-*N* signal x from $M < N$ measurements (the vector **y**). Since $M < N$, this problem appears ill-conditioned [2]. If, however, x is *K*-sparse and the *K* locations of the nonzero coefficients in s are known, then the problem can be solved provided $M \geq K$.Direct construction of a measurement matrix φ [3][4] such that $A = \varphi\psi$ has the Restricted isometry property for each of the$\binom{N}{K}$ possible combinations of *K* nonzero entries in the vector **v** of length *N*. However, both the Restricted isometry property and incoherence can be achieved with high probability simply by selecting φ as a random matrix.

3) *DESIGNING A SIGNAL RECONSTRUCTION ALGORITHM*

Optimization based on the *l*1 norm can exactly recover *K*-sparse signals and closely approximate compressible signals with high probability using only $M \geq cK \log (N/K)$[5]. This is a convex optimization problem that conveniently reduces to a linear program known as basis pursuit whose computational complexity is about *O (N*3*)*.

II. LITERATURE REVIEW

Sr. No.	References	Evaluation Approach
1.	Daniel Romero, Roberto L´opez-Valcarce. (2010).	It presents that comp ressive sensing is applied on wideband spectrum that means to determine the occupancy of channels spanning a broad range of frequencies.
2.	Ehab Ahmed Sobhy, Xi Chen,Zhuizhuan Yu.(2013).	This paper presents a sub-Nyquist rate data acquisition front-end based on compressive sensing theory.

3.	Thong T. Do.(2012)	This paper introduces a new framework to construct fast and efficient sensing matrices for practical compressive sensing
4.	Haifeng Zheng,Shilin Xiao.(2013)	In this paper, with the assumption that sensor data is sparse we apply the theory of CS to data gathering for a WSN where *n* nodes are randomly deployed.

III.PROPOSED METHOD

Fourier is the sensing domain for MRI images but Compressive sensing requires sparsity in any orthonormal transform domain. To prove that the image is sparse in any transform domain ψ an approximation to the image is generated using a separation of largest transform coefficients from fully sampled image.

If an image needs major coefficients to represent it, the image is still the same then why there is a need for reducing number of transform coefficients? All these answers lie in the idea that the optimal method for sparsifying images would be the one which maximizes the chance that only the right coefficients will be selected.

Experiments were done on MRI images of different image sizes. From fully sampled images, main coefficients were taken and the rest of them were unused. Images were reconstructed again to estimate the sparsity using orthogonal matching pursuit reconstruction algorithm. Results were compared with the original images to determine the quality of the recovered images in different domains. All the experiments were done in Discrete Cosine Transform (DCT) and Discrete Fourier Transform (DFT) to analyse how sparsity of MRI images varies in different transform domains and the qualitative parameters were measured.

IV. RESULTS

A. QUALITATIVE MEASURES

To quantify the structural differences between a distorted image and original image, different properties of the human visual system are used. The quality of reconstructed images is evaluated using parameters like Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR) and reconstructed time.

1) *Mean Square Error is obtained by the relation,*

$$MSE = \frac{1}{N^2} \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} ||x(i,j) - y(i,j)||^2$$

where $x(i,j)$ and $y(i,j)$ are original and reconstructed images, respectively, of size $N \times N$ and i and j are the pixel indices.

2) *Peak signal to noise ratio ,*

$$\frac{PSNR = 10\log(2^n - 1)^2}{MSE}$$

TABLE I: Comparison in Transform Domains.

TRANSFORM DOMAIN	MSE	TIME	PSNR(dB)
DCT	0.053607	0.0076	30.91183
DFT	0.8929	0.014	25.62855

CONCLUSION

MRI images were represented in two different domains i.e. in Discrete Cosine

Transform and Discrete Fourier

Transform.

A suitable measurement matrix was chosen which satisfies the Restricted isometry property. Reconstruction algorithm was used to obtain the reconstructed image and qualitative parameters were measured. Comparing the reconstructed image in two domains, it is observed that Discrete Cosine transform shows better performance than Discrete Fourier transform.

REFERENCES:

1. D.L. Donoho, “Compressed sensing,” IEEE *Transactions on Information Theory*, vol. 52, pp. 1289–1306,Apr. 2006.

2. M.A. Davenport, P.T. Boufounos, M.B.Wakin, and R.G.Baraniuk, “Signal processing with compressive measurements,”*IEEE Journal on Selected Topics in Signal Processing*, vol. 4, no. 2, pp. 445–460, Apr. 2010.

3. Desai Siddhi1 and Nakrani Naitik," Improved Performance of Compressive Sensing for Speech Signal with Orthogonal Symmetric Toeplitz Matrix," *International Journal of Signal Processing, Image Processing and Pattern Recognition*, Vol.7, No.4 (2014).

4. Amanjot Kaur 1, Jaspreet Kaur ," Comparision of Dct and Dwt of Image Compression Techniques," *International Journal of Engineering Research and Development* ISSN: 2278-067X, Volume 1, Issue 4 (June 2012).

5. Sumit Budhiraja, Dipti Bhatnagar," Compressive Sensing Techniques for Image Compression," *International Journal of Engineering Research and Applications* (IJERA), Vol. 1, Issue 4.

6. Fuleah A.Razzaq, Shady Mohamed," Non-Uniform Sparsity in Rapid Compressive Sensing MRI", *IEEE International Conference on Systems, Man, and Cybernetics,* October 14-17, 2012.

7. Rashid Ansari," Adaptive Hierarchical Data Aggregation using Compressive Sensing (A-HDACS) for Non-smooth Data Field," *IEEE ICC 2014 - Ad-hoc and Sensor Networking Symposium* 2014.

8. Jia (Jasmine) Meng," Compressive Sensing Based High-Resolution Channel Estimation for OFDM System," *IEEE JOURNAL OF SELECTED TOPICS IN SIGNAL PROCESSING,* VOL. 6, NO. 1, FEBRUARY 2012.