Compressive Sensing a New Approach For Data Compression: A Review

Khushboo Nibheriya
Assistant Professor, Electronics & Communication
Arya College of Engineering & I.T.
Jaipur, India
khushboonibheriya.ec@aryacollege.in

Vivek Upadhyaya
Assistant Professor, Electronics & Communication
Arya College of Engineering & I.T.
Jaipur, India
vivekupadhayaya.ec@aryacollege.in

Abstract— As we know that for data compression generally Shannon – Nyquist theorem taken in to consideration. But a severe problem which is associated with the traditional theory is the storage problem. According to this theorem the sampling rate must be twice the largest frequency component of the signal which we want to reconstruct. Due to this the data which is required to transmit a signal or to store it is too large. So to overcome this problem a new method is proposed, which is known as Compressive sensing. The sampling rate which is required reconstruct the signal is comparatively low in the compressive sensing. The various aspects about the compressive sensing and literature review with some important properties is given below.

Keywords- *Compressive Sensing(CS),Restricted Isometry Property (RIP)*

*****

I. INTRODUCTION

A new conventional technique is developed for reconstruction the original signal from high coefficient data under the Shannon sampling theorem, in which it give a new outlook that the sampling rate of the signal must be required twice the highest frequency. In the same case of linear algebra recommended that the all received measurement of a discrete finite-dimension signal must be large as its dimension for a proper reconstruction of a any type of signal like audio signal, image signal, video signal.

This describe principal followed by the most of the new technology based devices like digital to analog conversion , analog to digital conversion and medical imaging. The modern theory of compressive sensing gives a new scenario to data acquisition which opposed to this simple wisdom. In which the signal is reconstruct to the original signal from the highly incomplete measurement coefficients (information).

Some lossy compression techniques like JPEG and MP3 depends on the practical observation in which any kind of signal can be calculated by the small number of non zero measurement sample. A compression is acquire by the hold the all non zero coefficients and discard the all zero coefficient to make a easy strategy. Whenever signal is obtain by the some difficult costly, lengthy calculation procedure, which is fully wastage of resources. Hence some effort is applied on the signal to collect the full information and later on this information is emit at the stage of compression. In the compressive sensing is down to earth way is used to received compressed data by the holds only small number of measurement from high measurement sample.

The measurements are designed easily with the help of basis matrix in the compressive sensing. So compressive sensing used many applicable tools. The main feature behind of the compressive sensing that it can be able to reconstruct the original signal by using efficient algorithm

II. LITERATURE SURVEY

In the paper of G. Baraniuk, IEEE 2007 [1] used a new method to obtain and describe the compressible signal under the Nyquist rate, in which it utilize non adaptive linear projection that protect the structure of the signal and these original signal is captured and reconstructed from the linear projection with help of optimization process. Author show the result thru this paper that compressive sensing techniques employ on the sparse signal and compressible signal that can be presented by the non zero (K) high measurement from the all possible sample measurement (N) with it have large bandwidth.

The author J. Candes and B. Wakin, IEEE 2008 present a two protocols, first is Sparsity and second is Incoherence which are used to reconstruct the audio signal , image signal and video signal from the small number of measurement[2]. Sparsity provide the information rate of the continuous signal it must be small as compare to suggested bandwidth. Incoherence gives the fact of sampling/sensing waveform are extraordinary express by ψ. The main result of this paper by using these protocols, to obtain the intelligent information in the sparse signal without any distortion.

In the digital communication the reconstruction of the signal from the partial frequency at receiver side is discussed by J. Candes, J. Romberg and T. Tao, IEEE 2006 [3]. The author give the fact that signal is completely reconstructed the original signal by the using convex optimization, in which the result came out to the non linear sampling theorem. This theorem states that any kind of signal collect $(|T|)$ spikes may be reconstructed by convex optimization from all frequency sample sets which have a size $(|T| * \log N)$.

G. Shi, C. Chen, J. Lin, X. Xie, and X. Chen, IEEE 2012. Introduced the narrowband detection with high potential for obtain the high resolution in the comparison of kind of broadband detection. [4].In the paper author used the sparse representation and compressed sensing, singular valve decomposition to obtain the original signal, Which find out the powerful signal distortion. We are capable to recover the stable and accurate signal by using narrowband technique.

G. Shi, J. Lin, X. Chen, F. Qi, D. Lin, and Z. Li, IEEE 2008 [5] work on compressive sensing theory which are used for sampling the UWB (Ultra Wide Band) echo signal. The signal is recovered if the signal rate is smaller than the Nyquist rate. In the compressive sensing theory the performance and detection of the signal, Firstly the basis matrix is constructed by using matching rates to obtain the sparse signal which are most important approaches in the compressive sensing theory and second, to design the UWB signal detection in the theory of compressive sensing by using matching basis function with the help of analog to information converter. The author says that UWB signal are captured ,sampled and in the system without any high frequency analog to digital converter.

As per paper are describe that the principal component are achieved from the principal analysis component (PCA) of any kind of low resolution signal like image, audio and video signal [6] . The high efficient calculation is achieved whenever PCA applied on the particular image pixel, most of the contribution of the image pixel is relate sto the major principal components.

III. PRINCIPLES OF COMPRESSIVE SENSING

In the compressive sensing most of two principal are important first is sparsity, In which it belongs to signal nature like interest and second is incoherence that tell the how the signals are sampled and sensed by the system. If the system is fully respond and satisfied the incoherence property then signal can be possible to reconstruct the original signal from the small number of measurement. These type of measurements compressed the original signal, which can be recovered from the compressible signal.

A. Sparsity:

In the compressive sensing introduced on the signal, that are sparse. The signal are composed many component. Some component highly nonzero valve, which are used to recover the original signal and some are equal and close to the zero value, which are discarded.

B. The Concept of Coherence

In the theory of compressive sensing coherence was proposed in a general ground work in [7], and since that time it has been used extremely in the sparse representation of the signals. This is used to calculate the sub optimal algorithms ability like matching pursuit and basis pursuit for easily and accurate recognize the sparse signal representation. The matrix of measurement elements have uncorrelated columns that presumption are take advantage in the field of compressive sensing and sparse reconstructions.

To define the coherence or mutual coherence of the matrix B is expressed by the value of cross-correlation element of the matrix columns of B. Suppose b_1, b_2, b_3...... b_n be the column value of the A matrix, which take a normalized value like $b_l^T b_m = 1$, the mutual coherence of B is expressed as a

$$\mu(B) = \max_{1 \le l \ne m \le n} |b_l^T b_m| \quad (1)$$

B lower bound is

$$\mu(B) \ge \sqrt{\frac{N-g}{g(N-1)}} \quad (2)$$

If the μ (*A*) is small we can say dictionary is incoherent. We can say that a dictionary is incoherent if μ (*A*) is small. For the standard result it's necessary that the measurement matrix follow the incoherence property and RIP property. If the dictionary G is extremely coherent, then the matrix BG will be coherent.

Coherence is the most important property in the theory of compressive sensing groundwork. If the column element of the matrix are correlated then its not possible to differentiate the energy in the signal where it comes out from one or another.

To understand the theory we take a example, suppose that we are not under sampling and B is a identity matrix then we defined as given below

Y=GX

Let the first two columns are similar, $g_1 = g_2$. Then the measurement value g_1 can be defined by the first input vector (0, 1 , ... 0) or (1, 0, ... 1) or any convex combination. So here in the example this signal has not a common sparse hence signal is not recovered from the measurement sample

y=BGX.

C. The Restricted Isometry Property

An orthogonal matrix is square matrix in the linear algebra whose column and rows elements are orthogonal unit vector with real entity.

$$B^T B = B B^T = I$$

Where I is a identity matrix.

This phenomena is leads to describes the characterization: A given matrix B is orthogonal if the matrix transpose is equal to inverse that is

$$B^T = B^{-1}$$

The predicate of orthogonal matrix have two values that is either +1 or −1. An orthogonal matrix store the dot product of the vector in a pre-describe linear transformation, which acts as Isometry of Euclidean space, like reflection or rotation.

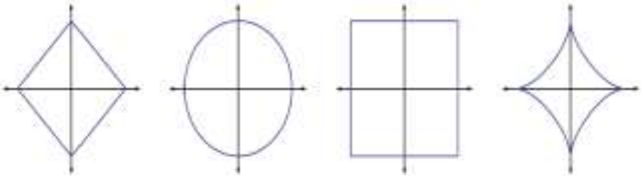

Figure 1. Unit Spheres in R^2 for the l_p norms

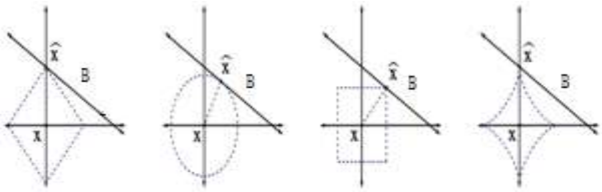

Figure 2. Best approximation of a pint R^2 by a one-dimensional subspace using l_p norms

The most important theorem is restricted Isometry property in the compressive sensing, which are used to represent the matrices. This matrix is orthogonal, when its column value performs by the sparse vector. This theory are used in the paper of Emmanuel Candès and Terence Tao [8] in the compression sensing . Some matrices which are used for the compressive sensing is bounded with RIP constant (NP Hard Bound), but some of the matrices are not bounded with this RIP constant. These matrices have been represented with high exponential probability, Bernoulli, Random Gaussian and Fourier matrices are fully response the RIP property in the compression, which have linear measurement of sparse level.

Let B is a $n \times p$ matrix with $1 \le s \le p$ integer. In the theorem if a constant is exits that is shows by δ_s for each $p \times s$ Sub-matrix B_s of B and every y vector,

$$(1-\delta_s)\|y\|_{l_2}^2 \le \|B_s y\|_{l_2}^2 \le (1+\delta_s)\|y\|_{l_2}^2 \qquad (3)$$

Then the matrix B is fully satisfies the Restricted Isometry Property with restricted Isometry constant.

IV. PROCEDURAL STEPS OF COMPRESSIVE SENSING

The execution steps of the compressive sensing are follows as below [9]:

1) Choose a convenient wavelet function and arrange the necessary decomposition level, after that operation performs on wavelet packet foil decomposition on any image signal and music signal.
2) Resolve the optimal basis of the wavelet packets under the theory of Shannon entropy.
3) During this period, the important information and energy of the signal is direct relate to the low frequency sub band with the wavelet packet transform, which give a important contribution in reconstruction of any kind of signal. In that signal are fully compressed without any loss of information, in which all the small frequency component are discarded.
4) Further the ground work of the compressive sensing, choose convenient random measurement matrix and encode the all coefficient value of high frequency in the signal with the best evaluation basis of the wavelet packet and achieve the coefficient value.
5) Store the all non zero and zero coefficient element from the all sampled coefficient by using OMP method.
6) Take a inverse wavelet transform to the store non zero and zero element in the signal and then the original signal will be reconstructed.

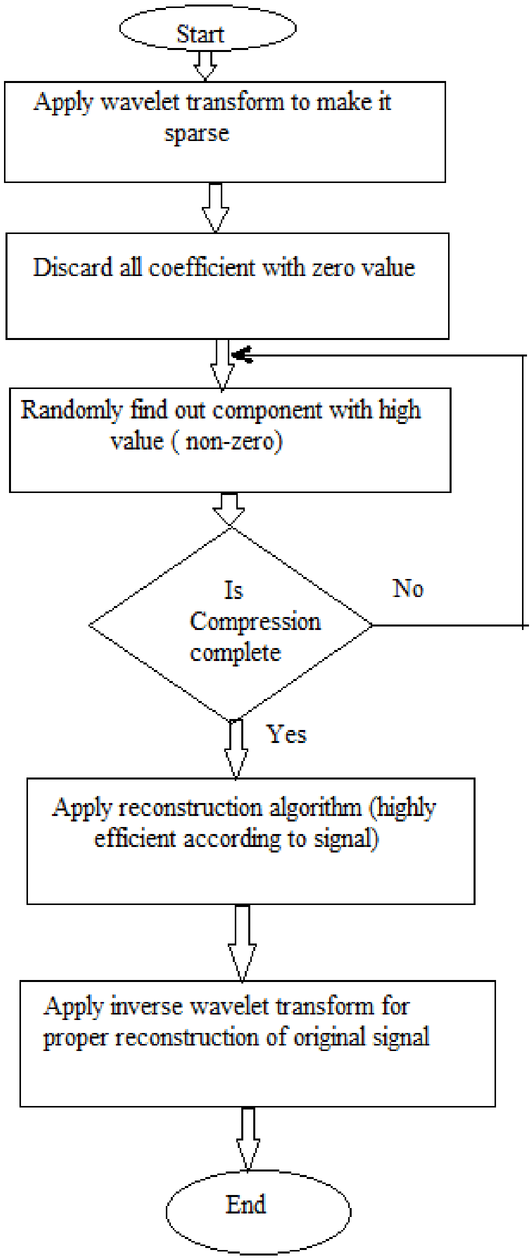

Figure 3. Flow chart of Compressive Sensing

V. CONCLUSION

The study which is done by us here is about the procedural overview and advantages of Compressive sensing over the conventional methods for compression. Various reconstruction algorithms are present in the literature survey. All are based on the sensing and measurement matrices. If we change the sensing and measurement matrices then we can improve the quality of reconstruction. The two parameters which are used widely for the performance evaluation of compressive sensing are Signal to Noise Ratio (SNR) & MSE (Mean Square Error). The basic problem with the compressive sensing is about Adaptability, which means we have to change the basis and measurement matrix in the manner that we can get maximum high value components from the signal. So we can get proper reconstruction. This theory is very much useful and can overcome various problems associated with conventional theory.

References

[1] G. Baraniuk, “Compressive Sensing,” IEEE Signal Processing Magazine, vol. 24, no. 4, pp. 118–121, Jul. 2007.

[2] J. Candes and B. Wakin, “An introduction to compressive sampling,” IEEE Signal Processing Magazine, vol. 25, no. 2, pp. 21–30, Mar. 2008

[3] J. Candes, J. Romberg, and T. Tao, “Robust uncertainty principles: Exact signal reconstruction from highly incomplete frequency information,” IEEE Transactions on Information Theory, vol. 52, no. 2, pp. 489–509, Feb. 2006.

[4] G. Shi, C. Chen, J. Lin, X. Xie, and X. Chen, “Narrowband Ultrasonic Detection with High Range Resolution: Separating Echoes via Compressed Sensing and Singular Value Decomposition,” IEEE Transactions on Ultrasonics, Ferroelectrics and Frequency Control, vol. 59, no. 10, pp. 2237–2253, Oct. 2012.

[5] G. Shi, J. Lin, X. Chen, F. Qi, D. Liu, and Z. Li, “UWB echo signal detection with ultra-low rate sampling based on compressed sensing,” IEEE Transactions on Circuits and Systems II: Express Briefs, vol. 55, no. 4, pp. 379–383, Apr. 2008.

[6] I. Jolliffe, Principal Component Analysis, 2nd, Berlin: Springer- Verlag, 2002.

[7] Candes, E.J. and Tao, T. (2005) Decoding by Linear Programming. IEEE Transactions on Information Theory, 51,4203-4215.

[8] Donoho, D.L. (2006) Compressed Sensing. IEEE Transactions on Information Theory, 52, 1289-1306.

[9] Kanike Vijay Kumar & K. Suresh Reddy “Compressed Sensing for Image Compression Using Wavelet Packet Analysis”, Vol 2, pp 155-159.