ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 2, Issue 9, September 2013

Reconstruction Using Compressive Sensing: A Review

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Abstract: Compressive sensing is a new type for signal reconstruction, which predicts that sparse signals and images can be reconstructed from what was previously believed to be incomplete information.. The theory has many potential applications in signal processing and imaging. In this paper we will present the compressive sensing research of various researchers.

Keywords: Compressive sensing, Sparsity, Incoherence, Nyquist.

I. Introduction

The traditional approach of reconstructing signals from processed data obeys the well-known Shannon sampling theorem "which states that the sampling rate must be twice the highest frequency" ((i.e., fs-⩾2fm,)). For this approach a large number of samples are required. Similarly, the fundamental theorem of linear algebra suggests that the number of collected samples (measurements) of a discrete finite-dimensional signal should be at least as large as its length (its dimension) in order to ensure reconstruction. In other words the accuracy of above two traditional theorems are directly proportional to the number of samples i.e., more sample means more accurate results. But now a day's the invention of a pretty technique named as Compressive sensing (CS) provides a new way to reconstruct signals using fewer number of samples (at lower rate). CS also helps to solve image processing and computer vision problems.The novel theory of compressive sensing (CS)- also known under the terminology of compressed sensing, compressive sampling or sparse recovery. CS integrates the math with statistical facts.

CS offers a new fantastic way to manipulate multiple observations of the same field view, allowing us to reconstruct low level details, which is impossible with standard compression methods.

Compressed sensing is a signal processing technique to encode analog sources by real numbers rather than bits, dealing with efficient recovery of a real vector from the information provided by linear measurements. By leveraging the prior knowledge of the signal structure (e.g., sparsity) and designing efficient non-linear reconstruction algorithms, effective compression is achieved by taking a much smaller number of measurements than the dimension of the original signal.

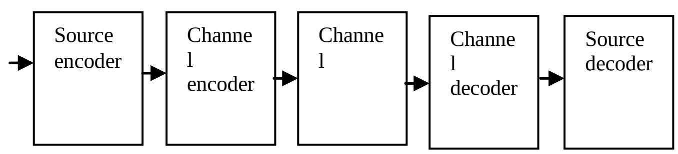

Fig1. Block Diagram of compressive sensing

II. Literature Survey

Two popular reconstruction algorithms for CS are basis pursuit (BP) and matching pursuit (MP). Basis pursuit is the mathematical optimization problem of the form:

$$\min \|x\|_1 \quad \text{subject to } y = Ax \quad x$$

where x is a $N \times 1$ solution vector, y is a $M \times 1$ vector of observations, A is a $M \times N$ transform matrix and $M < N$. It is usually applied in cases where there is an underdetermined system of linear equations $y = Ax$ that must be satisfied exactly& the sparsest solution in the L1 sense is desired.

Though MP is a heuristic algorithm, it provides comparable and sometimes more accurate results in reconstructing the noiseless input. In the noisy signal reconstruction case, reconstruction by both BP and MP contains errors that, though small, may not be acceptable [1].

An attempt has been made to present CS fundamentals and the implementation of CS reconstruction by BP and MP. Though MP is a heuristic algorithm, it provides comparable and sometimes more accurate results in reconstructing the

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noiseless input. In the noisy signal reconstruction case, reconstruction by both BP and MP contains errors that, though small, may not be acceptable [2].

In [3], author presented the use of compressive sensing and sparse representation with regards to image enhancement, restoration and classification.

The simplest greedy algorithm, orthogonal matching pursuit (OMP) , selects one coefficient at a time to include in the support of β. In particular, at each step it creates a residual by taking the projection of y onto the complement of the space spanned by the columns already included in the model, and adds to the model the column which has the highest inner product with this residual (i.e., forward selection) [4].

Yihong Wu presented a statistical (Shannon) study of compressed sensing, where signals are modeled as random processes rather than individual sequences. This framework encompasses more general signal models than sparsity. Focusing on optimal decoders, Yihong Wu investigated the fundamental tradeoffs' between measurement rate and reconstruction fidelity gauged by error probability and noise sensitivity in the absence and presence of measurement noise, respectively [5].

III. PRINCIPLE OF COMPRESSIVE SENSING

CS relies on two principles: sparsity, which pertains to the properties of natural signals of interest, and incoherence, which involves how signal is sensed/sampled. The basic principle is that sparse or compressible signals can be reconstructed from a surprisingly small number of linear measurements, provided that the measurements satisfy an incoherence property. Such measurements can then be regarded as a compression of the original signal, which can be recovered if it is sufficiently compressible.

***Sparsity*:**

In particular, many signals are sparse, that is, they contain many coefficients close to or equal to zero, when represented in some domain.

Incoherence:

Incoherence extends the duality between time and frequency. It expresses the idea that objects having a sparse representation in Ψ must be spread out in the domain in which they are acquired. This is similar to the analogy in which Dirac or a spike in the time domain is spread out in the frequency domain. Incoherence is necessary for acquiring good linear measurement in the new measurement space.

IV. STEPS OF COMPRESSIVE SENSING

The implementation steps of the algorithm are as follows [6]:

1) Select an appropriate wavelet function and set a required decomposition level, then execute the wavelet packet foil decomposition on the original image.

2) Determine the optimal basis of the wavelet packet in the light of the Shannon entropy criterion.

3) As the main information and energy of the original image are concentrated in the low-frequency subband by the wavelet packet transform, which plays a very important role in the image reconstruction, all the low-frequency coefficients are compressed losslessly in order to reduce the loss of the useful information.

4) According to the theory of CS, select an appropriate random measurement matrix, and make measurement encoding on all the high-frequency coefficients in line with the optimal basis of the wavelet packet, and obtain the measured coefficients.

5) Restore all the high-frequency coefficients with the method of OMP from the measured coefficients.

6) Implement the wavelet packet inverse transform to all the restored low-frequency and high-frequency coefficients, and reconstruct the original image.

V. CONCLUSIONS

In this review paper authors made an attempt to define compressive sensing technique, its application compressive sensing and the steps involved in compressive sensing technique. The principle and flow chart so discussed to provide guideline in research work. The attempt has beebn made to find gap in existing literature. Compressive sensing relies on the fact that most analogue signals have a structure of some kind that can be exploited to reconstruct them. Know this structure and the signal can be reconstructed using a sampling rate that is significantly lower than the Nyquist rate.

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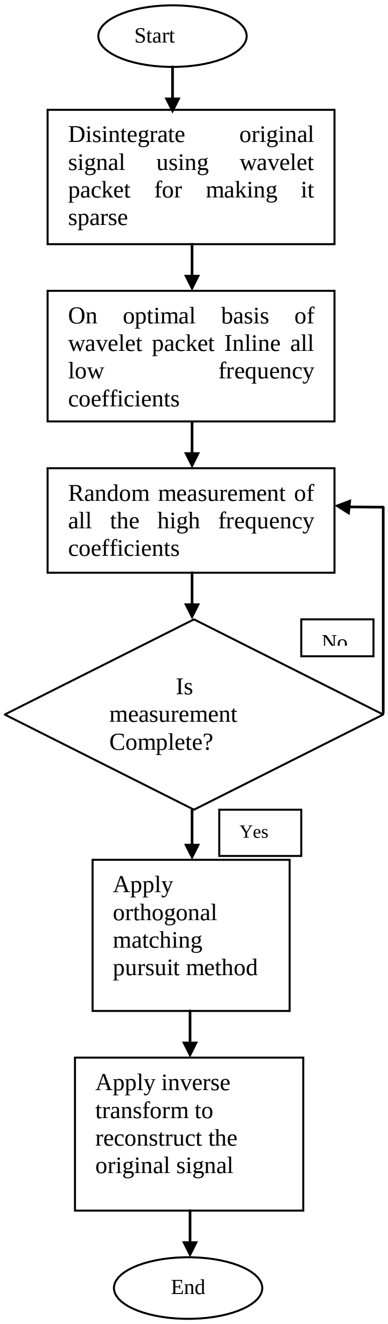

Fig2. Flow chart of compressive sensing

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