National conference on Technology innovation in Mechatronics,Energy Management and Intelligent communication(NCTIMEMIC-2017)

International Journal of Advanced Scientific Technologies , Engineering and Management Sciences (IJASTEMS-ISSN: 2454-356X) Volume.3,Special Issue.1,April.2017

Survey on Signal-Reconstruction in Compressed Sensing

Anjaly Krishnan,PG student ,College of Engineering Kidangoor
Rajalakshmi.s,PG student ,College of Engineering Kidangoor

Abstract—In this modern years compressive sensing (CS) has a very important and valuable attention in the areas of Computer vision problems, Applied mathematics, Signal processing, Optical engineering ,even in Biomedical imaging also CS has a considerable attention. The main concept about these CS is that we can represents most of the signals with only a few number of non-zero coefficients in a advisable dictionary or basis. Once we construct a signal using compressive sensing reconstruction is also needed. There, variety of reconstruction algorithms are used in the area of CS.In this paper I include a survey on reconstruction methods used in compressive sensing research of various researchers.

Index Terms— Compressive Sensing, Sparsity, Incoherence, Nyquist , Basis pursuit, OMP ,MP, STGP

I.INTRODUCTION

We know that all traditional electronic equipment such as digital camera, electronic measuring instruments etc: working in the basis of Shannon Sampling theorem for signal acquisition,which states that sampling rate must be twice the highest frequency (fs>= 2fm).Otherwise we cannot reconstruct the original signal. So that we need a large number of samples for reconstruction .Similarly the fundamental theorem of linear algebra says that the number of collected samples of a discrete signal should be greater than it's length. Then only can reconstruct the original information So can concluded that the accuracy of above two methods are directly related to the number of samples. That is if the number of samples collected are large then accuracy also very high. In generally can says that more samples means more accurate results. But in most of the case we does not get such larger amount of samples .There by cannot retrieve back the original signal in a proper manner,to solve such difficulties modern field of communication technologies introduced a new type of signal reconstruction technique called compressive sensing.

Compressive sensing technique provides a better and new way to reconstruct the original signals using fewer number of its samples. Compressive sensing techniques also helps to solve the problems in image processing and computer vision fields (accruing, processing, analyzing and understanding digital images).Using Compressive sensing one can recover back the original input signals and images from fewer measurements or samples than that of traditional methods. To make this possible we should know about two terms, Sparsity and Incoherence.

If the expansion of the original signal or image as a linear combination of the selected basis functions has many zero coefficients, then it's often possible to reconstruct the signal exactly. This is the main concept of sparsity.In simply can says that the signal can represented as matrix with most of it's coefficients are equal to be zero. And according to incoherence a sensing waveform have extremely dense representation in its domain.

A. *Traditional sensing and Compressive Sensing*

The basic difference between traditional sensing and compressive sensing are expressed in Figure 1(a.b)

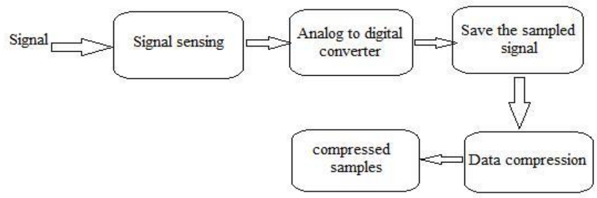


Fig.1.a:-Traditional sensing

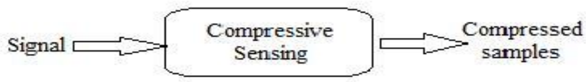


Fig.1.b:-Compressive sensing

In traditional signal sensing techniques we use sampling as a main part.And it works based on Shannon-Nyquist theorem.The theorem states that to restore a signal exactly and uniquely, you need to have sampled with at least twice its frequency.[1] and in compressed sensing we will take the signals as sparse. All ready mentioned that CS working based on spare representations and incoherence. Sparsity gives fractions of non-zero elements over total number of elements. In generally many signals are considering to be sparse ,that is most of the coefficients are close to zero or equal to zero, when we are representing these in some domain.

In spare representation

- The signal is characterized by fewer coefficient
- Compression capabilities
- fast algorithms and memory savings.

Like sparsity incoherence is also considering as a main factor for CS. Which extends duality between frequency and time. Using this we can says that object having sparse representation in some domain (mainly basis Ψ),will spread out in the domain from they are acquired. This condition is similar to a spike in time domain spread out in frequency domain. It is considering as an important factor for acquiring good linear measurements. But finding sparse solutions for s problems is a fundamental challenge in signal processing applications, from signal acquisition to source separation. In many areas, such as medical imaging or geophysical data acquisition, it is necessary to find sparse solutions to understanding the problems. There for fast methods have to be developed. There are different methods are used to encrypting and decrypting the signals using Compressive Sensing methods.

II. LITERATURE SURVEY

After learning more about compressive sensing I mainly concentrated the reconstruction algorithms used in these areas, and I understood that there are a large variety of algorithms used for recovery of the signals.

- Basis pursuit algorithm
- Matching pursuit
- Orthogonal matching pursuit
- Stage wise gradient pursuit

.l1 magic is considering as the first step in reconstruction algorithms.[2],and figure 2 represents the orginal and properly reconstructed signals using l1 magic.

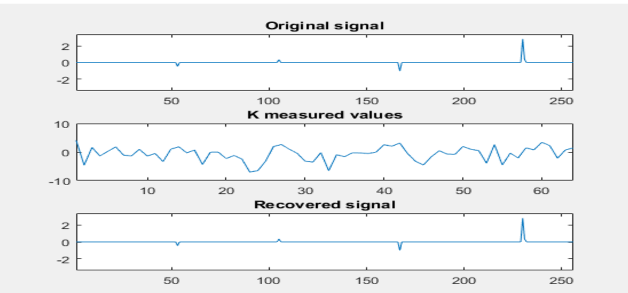


Fig.2 l1 magic algorithm

Basis pursuit is the mathematical optimization of a problem in the form of

min ‖ x ‖ 1 subject to y= Ax , where

x= signal
y=measurement vector
A=sensing matrix

These type are mainly used in cases where there is a undetermined signals of linear equation of y=Ax

There is an experimental result[3] to understand the basic of CS using basis pursuit algorithm.Here 2000msamples of the data is taken.Using basis pursuit,at different sparsity level they tried to reconstruct that 2000 samples and accuracy also calculated against each sparsity values. Figure 3 represents reconstructed output using BP algorithm and table 1 represents sparsity values and respective accuracy.

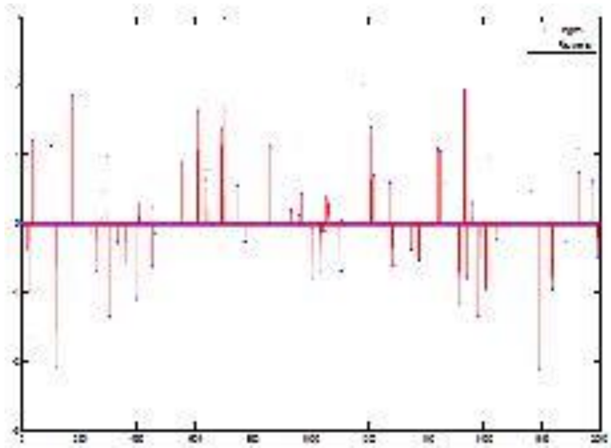


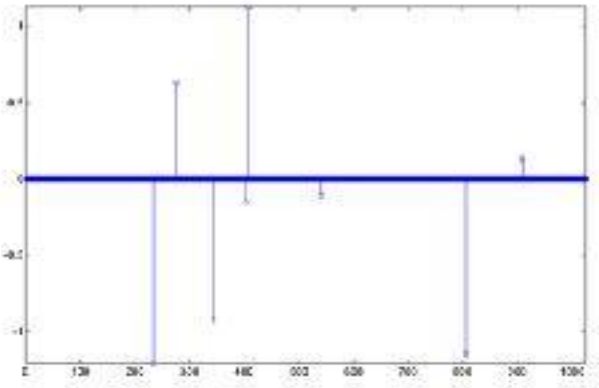
Fig 3,reconstructed output data using Bp

Sr. No.	Sparsity	Accuracy
1	50	$5.7753*10^{-6}$
2	30	0.0979
3	70	$2.2136*10^{-6}$

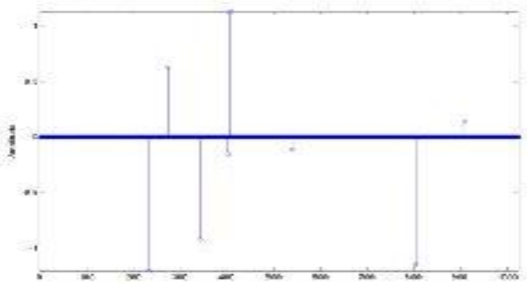
Table 1,sparsity level Vs accuracy

Using these result we can conclude that when sparsity level increases accuracy decreases and will get approximately accurate signal. BP algorithm has application mainly in image processing for de-noisy purpose and in communication areas.

Matching pursuit[4] is the next one used for reconstruction of signals.It considering as a class of iterative algorithm that decomposes the signal into linear expansions of function, And that functions forms a dictionary.MP was first introduced by Mallat and Zhang and it is closely related to projection pursuit regressions.Fig.5 shows reconstruction of a signal using MP.



(a)



(b)

Fig 5 Reconstruction of signal using MP

(a)Original signal
(b)Reconstructed signal

Using MP method it provides more accurate results in reconstruction side with noiseless input.If the input signal contains noise then both basis and MP will give error output.

Orthogonal matching pursuit[5] is also a spare approximation algorithm. It include finding the best matching projection of data on to the span of over complete dictionary. Using this will get a better result than traditional matching pursuit method. It considering as a simplest greedy algorithm ,at a time only one coefficient is uses. Even if it create computational complexities of encoder. Fig.6 is representation of signals at different dimensions using OMP [5]

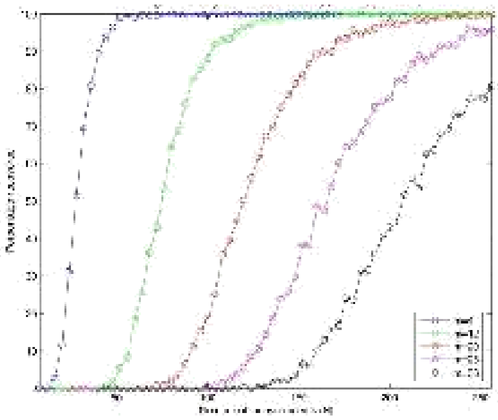


Fig.6 reconstruction of the signal using OMP

Next one is Stage wise gradient pursuit method[6].This is an improved form of OMP. Here we use gradient pursuit algorithm and binomial equations are used for solving underdetermined systems. Using this method we can reduce the time of reconstruction algorithm.

All these methods have its own advantages and disadvantages.Now a days, new type of method is also used known as sparse Kalman Tree Search (sKTS),that provide a robust reconstruction of the sparse vector when the sequence of correlated observation vectors are available.This algorithm builds on expectation maximization algorithm and consist of two main operations.

- Kalman smoothening
- Greedy tree search

III CONCLUSION

In this survey paper ,I made an attempt to define the CS technique,its applications and importance .Also made a comparison between different reconstruction algorithms used in this area.

ACKNOWLEDGMENT

We would like to acknowledge the funding provided from TEQIP phase II of college of Engineering Kidangoor for the publication of this paper.

REFERENCES

[1] Magic Reconstruction compressed sensing ,math works news and note-Cleve molerSpare signal reconstruction using Basis pursuit algorithm, Pallavi Dhole Supatana Auethavekiat" Introduction of CS" 39-46 jul.2010

[2] J A Tropp and A C Gilbert "Signal recovery from random measurement in OMP" IEEE Trans.53(12);4655-4666,2007

[3]Kanike Vijay Kumar and Suresh Reddy "Compression using Wavelet packet Analysis "Vol.2 ,pp 155-159

[4]E. J. Candes, J. Romberg, and T. Tao, "Robust uncertainty principles:Exact signal reconstruction from highly incomplete frequency information,"*IEEE Trans. Inf. Theory*, vol. 52, pp. 489–509, Feb. 2006.

[5] J. A. Tropp and A. C. Gilbert, "Signal recovery from random measurements via orthogonal matching pursuit," *IEEE Trans. Inf. Theory*, vol.53, pp. 4655–4666, Dec. 2007.

[6] D. Needell and J. A. Tropp, "CoSaMP: Iterative signal recovery fromincomplete and inaccurate samples," *Appl. Comput. Harmon. Anal.*,vol. 26, pp. 301–321, 2009.

[7] W. Dai and O. Milenkovic, "Subspace pursuit for compressivesensing signal reconstruction," *IEEE Trans. Inf. Theory*, vol. 55, pp.2230–2249, May 2009.

[8] J. Wang, S. Kwon, and B. Shim, "Generalized orthogonal matchingpursuit," *IEEE Trans. Signal Process.*, vol. 60, pp. 6202–6216, Dec.2012.

[9] S. Kwon, J. Wang, and B. Shim, "Multipath matching pursuit," *IEEE Trans. Inf. Theory*, vol. 60, pp. 2986–3001, May 2014.