Data Compression Using Compressive Sensing: A Review

[1]Preeti Kumari, [2]Gajendra Sujediya

[1]M.Tech Scholar, [2]Assistant Professor,
[1]Department of Electronics & Communication,
[1]Rajasthan Institute of Engineering & Technology, Jaipur, India

Abstract : Compressive sensing (CS) is the concept of reducing sampling rate of a signal. CS builds upon the fundamental fact that we can represent many signals using only a few non-zero coefficients in a suitable basis or dictionary. Nonlinear optimization technique enables recovery of such signals from very few measurements. While, the Nyquist's sampling theorem suggests that to have a lossless recovery of the original signal, it is necessary to sample the signal at frequency twice that of the maximum frequency of the signal. The major drawback is the requirement of huge number of samples in case of applications like: digital image, video cameras, high speed analog to digital convertors, imaging systems (medical scanners and radar). It reduces the required number of samples for signal representation at much lower rate than Nyquist's rate. High speed applications require high sampling rate that over burdens the role of ADC in signal processing. So in such cases compressive sensing plays a major role for improvement of performance. This combination gives an optimum value of Signal to Noise Ratio (SNR).

***IndexTerms* – Compressive Sensing (CS), Signal to Noise Ratio (SNR).**

I. Introduction

Conventional knowledge and many other common apply in acquisition and reconstruction of pictures from frequency information follow the fundamental principle of the Nyquist sampling theory. In recent years, compressed sensing (CS) has attracted wide attention in areas of applied math, and technology by suggesting that it's going to be attainable to surpass the standard limits of sampling theory. During this section, we offer associate in nursing up-to-date review of the fundamental theory underlying cesium. When a quick historical summary, we start with discussion of meagerness and different low-dimensional signal models. Then we tend to treat the central question of the way to accurately recover a high-dimensional signal from a tiny low set of measurements and supply performance guarantees for a range of thin recovery algorithms. We conclude a discussion of some extensions of the thin recovery framework. In subsequent chapters of the work, square measure going to see however the basics during this chapter are extended in several exciting directions as well as new models for describing structure in each analog and discrete-time signals, new sensing style techniques, additional advanced recovery results and rising applications.

Looking at all on top of points we tend to come with an answer in sort of "Compressive sensing". The thought of compressive sensing is employed to compress the signal before storing/transmitting [1][2]. The necessity of high operative speed ends up in high rate. Compressive sensing is one of the rising answer to attenuate the over burdening of system. This system is useful wherever the signal is sampled at a rate below than the Nyquist's rate [3][4]. It takes few samples rather than processing sizable amount of samples. These samples area represent the signal expeditiously. Thus, compressive sensing technique improves the process speed and will increase the storing capability of the system [5].

We are in the middle of a digital revolution which is driving the development and distribute systematically of new kinds of sensing systems with increasing the quality of being faithful and resolution. The pioneering work of Kotelnikov, Nyquist, Shannon, and Whittaker is the theoretical foundation of this revolution on sampling continuous-time band-limited signals [6, 7, 8, 9].Their results demonstrate that videos, images, signals and other type of data can be exactly recovered from a unique set of samples which are uniformly spaced taken very frequently called Nyquist rate of twice the highest frequency which is present in the signal of interest. Capitalizing on this most unique discovery, most of the signal processing has moved from the analog to another form which is digital domain and ridden the wave of Moore's law. Digitization is one of the most valuable works that has enabled creation of sensing and processing systems that are more robust, cheaper and consequently most widely used than their analog counterparts.

While going through this idea which has recently gained significant attraction in field of the signal processing community, over a great hints in this direction getting back as far as the eighteenth century. In 1795, for estimating parameters which are associated with a small number of complex exponentials sampled in the presence of noise, Prony has proposed an algorithm [10]. In the early 1900's the next theoretical leap came, when Caratheodory showed a positive linear combination of any k number of sinusoids which can be determined uniquely by its value at $t = 0$ and at any other 2k points in the time [11, 12]. Now this type of representation is few samples than the number of samples according to the Nyquist rate when k is assumed to be small and the range of expected frequencies is large. In the 1990's, George, Gorodnitsky, and Rao generalized this work, who had studied sparsity in the field like biomagnetic imaging and other contexts [13-15, 16]. Simultaneously, Bresler, Feng, and Venkataramani had proposed a new scheme of sampling, for acquiring a specific classes of signals having only k components with nonzero bandwidth (as contrast to pure sinusoids) with some restrictions on the possible signal spectral supports, although the accurate recovery was not guaranteed in general of original signal [17, 18, 19, 20]. In the early 2000'sMarziliano, Vetterli and Blu, developed methods of sampling for certain classes of signals which are of parametric nature , governed with only k parameters with highly importance, showing that sampling and recovery of the signals can be done from just 2k samples only [21].

II. LITERATURE REVIEW

An audio signal is a representation of sound, typically as an electrical voltage format. Audio frequency ranges roughly from 20 to 20,000 Hz (the limits of human hearing). Signals may be synthesized directly or may originate at a transducer such as a microphone, musical instrument pickup, phonograph cartridge, or tape head. Our work is mainly concentrated on non-speech audio signal. The reason for choosing an audio signal is that sparsity can be exemplified and also can be analyzed their degree of sparsity. Music signals are produced by various instruments each of them having their own operating frequency. The storage and exchange of signals requires compression.

Needell & Vershynin [22] presented the relation between L1-minimization method and iterative method for sparse signal recovery from an incomplete set of linear measurements. Regularized Orthogonal Matching Pursuit (ROMP) has better speed and transparency than Orthogonal Matching Pursuit (OMP). If the uniform uncertainty principle is satisfied by linear measurement then ROMP algorithm can reconstruct a sparse signal.

Sreenivas and Kleijn [23] showed possible recovery of compressive sensing signal (which is sparsely excited) even for unknown sparsely excited impulse response matrix. The method found joint estimation of both the impulse response and sparse excitation which found to be efficient due to matching pursuit.

Xu et al.[24] proposed a method to compress the non-stationary signal by compressive sensing using K-L transform. The method provides an observation of compressing the signal during the sampling only. The approximation of reconstructed signal in frequency domain, time domain and time-frequency domain was well defined. The simulation results validated the method on Linear Frequency Modulated (LFM).

Wang et al. [25] proposed hybrid dictionary function which combines DFT model and Linear prediction coding (LPC) as the basis for speech compression. The scheme employed Orthogonal Matching Pursuit (OMP) in hybrid dictionary domain for computation of sparse representation.

Bryan & Leise [26] in their work offers a convenient but conscientious and very needful self-contained narration of the main ideas in compressed sensing, aiming at non-connoisseurs and undergraduates who had some probability and linear algebra. The basic undertaking is first ornamented by contemplating the problem of perceiving a defective items which are few in set of a large items i.e. they are having a large set of defective items and they are searching few defective items among them. We then invigorate up the mathematical substructure of compressed sensing to reveal how combining effective methods of sampling with fundamental ideas from optimization, a bit of approximation theory, linear algebra and probability allow the appraisal of unknown quantities with very less sampling rate of data then conventional methods.

F. Duarte & C. Eldar [27] have worked with the random measurement matrix operator that can be replaced by sensing architecture which is highly structured , it has close similarity to the characteristic of realistic hardware. For sparsity in the standard form, prior has to be enlarged to include the richer signal class and broader data models to be encoded including signals in continuous time domain. In expressive overview, the essence is exploiting measurement structure and signal in the compressive sensing. In this review the author exercising in subsequent development theory and practice underlying CS: we specifically visualize extending the pre-existing frame to signal with broader class and motivating new design technique and implementation. Some of the examples mentioned previously throughout are ultrasound, MRI (which are medical devices), optical system cognitive radio and more. These gather well promised methodology for rethinking of several acquisition systems and extend the limit presently sensing capabilities. In this author also demonstrated, that the CS gathers the promise for improved resolution by elaborating signal structure. This thing can come with high revolution in many application like microscopy by efficient using the degree of freedom that is available for these technique. Many applications like radar, medical imaging, military surveillance , civilian surveillance and consumer electronics all rely on analog to digital converter and basically there are resolution-limited. So by removing Nyquist's constrain in these devices and increasing resolution make better experience of user, increasing imaging quality, improving data transfer rate and reducing exposure time.

Meinard et al.[28] in their paper furnishes a summary of some techniques of signal analysis that particularly address dimensions such as timbre, rhythm, harmony, melody. Now we will inspect how specific characteristics of music signals give their influence and ascertain these methodology and we are highlighting a number of unique music analysis and recoverable tasks that makes such processing possible. Our goal is to reveal that, to be triumphant, music signal in audio form processing methodologies must be enlightened by a unplumbed and thorough insight into the characteristic of music itself. Processing of music signal may be materialize to be the inferior relation of the mature and large field of speech signal processing, not minimal because many representation / procedures originally flourished for speech have been pertained to music with good results. However, the music signals possess desirable structural and acoustic characteristic that differentiate them non- musical signals or other spoken language.

Bello, [29] in his paper demonstrate a unique method for computing the structural correlation between music recordings. Here author used the recurrence plot analysis to specify patterns of recapitulation in feature sequence and the normalized distance of compression, a pragmatic estimation of the joint Kolmogorov complexity, to compute the pairwise correlation between the plots. By computing the distance between transitional portrayals of signal structure and suggested methods differ from general approaches to the analysis of music structure which actually assume music with block-based model and thus centralize on segmenting & clustering sections. The approach ensures that global structure is consistently designated in the existence of key changes, instrumentation and tempo while the used matrix furnishes a straightforward to compute robust and versatile substitute to general approach in music resemble research. In the end, experiment results reveal success at designate similarity, while accord an optimal parameterization of the recommended approach.

Urvashi et al. [30] in their paper, encapsulate the several approaches in the representation of speech signal in sparse domain. Each method discussed has its own advantages and disadvantages. Depending upon the prerequisite one could collect an accurate one. First one is straightforward and complexity less forms the point of view of execution while there are many ambivalences left unaltered. In the second techniques those restriction have been compensated but complexity has enlarged to a greater magnitude. In the third technique the triumph for obtaining the right degree of representation is not attained. It necessitates more advancement in the representation of unvoiced part of the speech that can strengthen execution of CS in this domain.

Yue et al. [31] proposed the Linear Prediction Coding (LPC) that is basically a very organized tool for the compression of the speech signal, because speech signal can be considered as AR process. In its voiced criteria the speech signal is assumed to be a quasi-periodic. Hence better approximations are provided by using basis as Discrete Fourier Transform (DFT). Thus this DFT model and LPC model both combined with the efficiently proposed hybrid dictionary, for which the speech signal is taken as basis one. To complete the sparse representation the Orthogonal Matching Pursuit (OMP) employed in the domain of hybrid dictionary in their simulation. In this paper, they introduce a unique framework in the regard of speech coding deployed on CS concept. The OMP algorithm is enlisted to solve the problem on the recovery side, offering a methodical estimation of norm minimization for decision making of the transform domains. It authorizes for a trade-off between the waveform sparse domains have an adequately perceptual quality on the basis of the hazardous selection. Basically the hybrid dictionary propounds substitute logic in the CS for construction of basis matrix in which the signal along with several characters may be represented in the sparse domain, creating it for possible adaptive choice. For next analysis, the premise for unvoiced section and comparative interpretation on its performance in comparison with other methodology are under examination.

Mads et al. [32] considered in this paper that the compressed sensing application (compressive sampling) to audio and speech signals. They discussed the design considerations and matters that must be taken in consideration in doing so, and they applied compressed sensing as a pre-processor to the decompositions in the sparse domain of real audio and speech signals using dictionaries that actually composed of windowed complex sinusoids. In their results, it is demonstrated that the postulates of compressed sensing can also applicable to sparse decompositions of audio and speech signals and also it provides a significant depletion of the complexity in the computational, but there is possibility for such signals may pose a provocation due to their complex and non-stationary nature with sparsity of varying levels.

In this paper, they have contemplated the application of the compressed sensing principles to audio and speech signals. More certainly they have analyzed this particular in the surroundings of decompositions in sparse domain, established on dictionaries containing of windowed complex exponentials. They have argued that serving as a pre-processor for sparse decompositions in the compressed sensing as the complexity of deciphering caused reduction in problems of convex optimization to a great extent in this process. Furthermore, their results reveal that sparse decompositions perform equally accurately with and without compressed sensing nevertheless of the presumed sparsity level. This is very important consideration as the sparsity level cannot be well known a priori and can vary over a time range for audio and speech signals. This actually means that decompositions in the sparse domain with compressed sensing functions, no worse than the sparse decompositions have done in the first place.

III. Compressive Sensing Theory

To address the challenges which are involved in dealing with logistical and computational such high-dimensional data, we generally depend on compression, which actually aims at finding the highly dense representation of the signal that is able to achieve a fine target level with some acceptable distortion. One of the most popular and valuable techniques for signal compression is known as transform coding, and distinctive relies on searching a basis or frame that provides sparse or compressible representations for signals which is in a class of interest . By taking the advantage of sparse representation, we mean that for a signal of length n, we can represent it only with k << n nonzero coefficients; by a technique called as compressible representation, we mean that the signal can be well-approximated by a useful signal with only k nonzero coefficients. Both compressible and sparse signals can be well represented with a great fidelity by preserving few of the values and locations of the largest coefficients of the signal. This most valuable process is called sparse approximation, and forms the foundation of useful technique called as the transform coding schemes that make fully use of signal sparsity and compressibility, including the standards like JPEG, JPEG2000, MPEG, and MP3.

Figure 1. CS Based Measurement

Figure 2. CS Reconstruction

A. Power Law

If any signal X is compressible then it will follow power law.

$$|X|_L \le C_r L^{-r} \tag{1}$$

$|X_L|$ is the largest value among all the values of X, provided that r >1, C_r is a constant and depends only on r [3]. This means that most entries of a compressible vector are small while only few entries are large. Such a model is appropriate for the wavelet coefficients of a piecewise smooth signal, for example. Here higher frequency signal are having small magnitude coefficients while low frequency component having large magnitude coefficients.

B. Sparse representation of signal

X is a real, finite length, discrete time signal. In vector form this signal can be represented in R^N vector space as the Nx1 column vectors like X [0], X[1],.......X [N]. Basis vector has this vector property by which any high dimension signal in vector space R^N can be represented in term of basis vectors $\{\Psi_i\}_{i=1}^{N}$. $\{\Psi_i\}_{i=1}^{N}$ are the columns of complete basis matrix ψ of order N x N.

$$X = \sum_{i=1}^{N} S_i \Psi_i \tag{2}$$

$$\text{Or } X = \Psi S \tag{3}$$

X is a representation of the signal in time or space domain while S is a representation of signal in basis matrix ψ domain. For sparse representation of signal X it is necessary that it must have few (K) large magnitude coefficients which must be retained and many (N-K) small magnitude coefficients which must be discarded. In these large magnitude coefficients (which represents K-sparse) signal structure must be preserved for accurate recovery of the signal. After acquiring the K-sparse signal these coefficients are encoded.

IV. RECOVERY VIA COSAMP

Here we are going to presents and analyses a unique algorithm of signal reconstruction that obtains these desiderata. The technique/algorithm is known as CoSaMP, from the matching pursuit of acrostic compressive sampling. As get the idea from the name, this new technique is basically realised on orthogonal matching pursuit (OMP), from the literature, it basically suggests many other concepts to accelerate the algorithm and furnish high guarantees that cannot achieved by OMP.

The overview of the algorithm is given in this section with some straightforward pseudo code. Major theorems presented on algorithm performance. Then it goes through deep meaning of bound and implementation of source.

A. Overview of CoSaMP

Algorithm of CoSaMP basically requires some piece of information as an input.

- Via matrix-vector multiplication to access the sampling operator.
- Unknown signal with noise sample vector.
- Approximated sparsity that to be produced.
- Criteria for halting.

Along with trivial approximation of signal the algorithm is initialized this making sense that the unknown target signal basically equal to the initial residual. The CoSaMP's pseudocode which exists in the algorithm is given below. The code is actually describing the class of algorithm that we examined in this work. Besides, there are many parameters which are adjustable, that can make performance better: the components those we selected at the step of identification and retained at pruning step.

IV. CONCLUSION

All signals in real world are non-stationary in nature. Application of sample and frame work on these is done based on windowing concept and also the compression is done with the help of direct transform. Through, our analysis we have projected that through compressive sensing, the amount of compression achieved is better and also the method is independent of the kind of signal and its characteristics. The major requisites for CS to work in order to obtain faithful recovery are satisfaction of RIP and Incoherence properties. The various combinations of sensing matrix and basis matrix are experimented and study in term of SNR obtained. As we saw that for particular sensing matrix there is basis matrix exists for which sensing matrix has dense representation in basis matrix.

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