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Compressive Sensing based Channel Estimation in OFDM Systems

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Abstract: Compressive Sensing (CS) is a new sensing modality, which compresses the signal being acquired at the time of sensing. Signals can have sparse or compressible representation either in original domain or in some transform domain. Relying on the sparsity of the signals, CS allows us to sample the signal at a rate much below the Nyquist sampling rate. Also, the varied reconstruction algorithms of CS can faithfully reconstruct the original signal back from fewer compressive measurements. This fact has stimulated research interest toward the use of CS in several fields, such as magnetic resonance imaging, high-speed video acquisition, and ultrawideband communication. This paper reviews the basic theoretical concepts underlying CS. To bridge the gap between theory and practicality of CS, different CS acquisition strategies and reconstruction approaches are elaborated systematically in this paper. The major application areas where CS is currently being used are reviewed here. This paper also Highlights some of the challenges and research directions in this field.

Index Terms: Compressive sensing, sparsity, CS acquisition strategies, random demodulator, CS reconstruction algorithms, OMP, CS applications.

I. INTRODUCTION

After the famous Shannon sampling theorem, introduction of compressive sensing (CS) is like a breakthrough in signal processing community. CS was introduced by Donoho,
Candès, Romberg, and Tao in 2004. They have developed its mathematical foundation. CS is basically used for the acquisition of signals which are either sparse or compressible. Sparsity is the inherent property of those signals for which, whole of the information contained in the signal can be represented only with the help of few significant components, as compared to the total length of the signal. Similarly, if the sorted components of a signal decay rapidly obeying power law, then these signals are called compressible signals, refer Fig.1. A signal can have sparse/compressible representation either in original domain or in some transform domains like Fourier transform, cosine transform, wavelet transform, etc. A few examples
of signals having sparse representation in certain domain are: natural images which have sparse representation in wavelet domain, speech signal can be represented by fewer components using Fourier transform, better model for medical images can be
obtained using Radon transform, etc. Acquisition of sparse signals using traditional methods require: i) sampling using Nyquist-criterion, which results in too many samples compared to the actual information contents of the signal, ii) compressing the signal by computing necessary transform coefficients for all the samples, retaining only larger coefficients and discarding the smaller ones for storage/transmission purposes. Addressing the question ``why to take too many samples, when most of them are to be discarded?", CS simplifies the signal acquisition by taking far fewer random measurements. Fig.2 depicts the comparison between traditional sampling and CS sampling schemes.

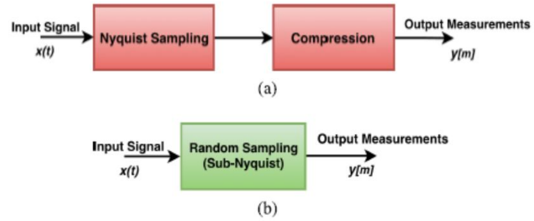

FIGURE 2. A comparision of sampling techniques: (a) traditional sampling, (b) compressive sensing.

Another limitation of sampling using Nyquist-rate is that the rate at which sampling must be done, may not be practical always. For example, in case of multiband signals having wide spectral range, sampling rate suggested by Nyquist criterion
may be orders of magnitude higher than the specifications of best available analog-to-digital converter (ADC).

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The sampling rate using Nyquist-criterion is decided by the highest frequency component present in signal, whereas, sampling rate in CS is governed by the signal sparsity.

The CS measurements are non-adaptive, *i.e.*, not learning from previous measurements. The resulted fewer compressive measurements can be easily stored or transmitted.

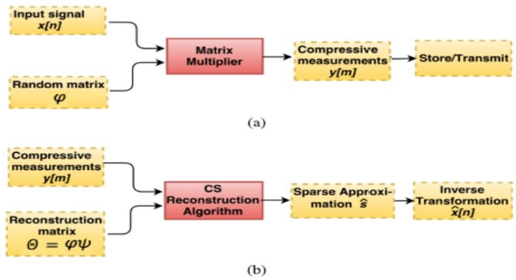

FIGURE 3. CS Model: (a) acquisition model, (b) reconstruction model.

It gives an impression of compressing the signal at the time of acquisition only and hence the name `Compressive Sensing'. CS allows the faithful reconstruction of the original signal back from fewer random measurements by making use of some non-linear reconstruction techniques. Because of all these features, CS finds its applications especially in the areas

i) where, number of sensors are limited due to high cost, *e.g.*, non-visible wavelengths, ii) where, taking measurements is too expensive, *e.g.*, high speed A/D converters, imaging via neutron scattering, iii) where, sensing is time consuming, *e.g.*, medical imaging, iv) where, sensing is power constrained.

A. Acquisition Model

CS works by taking fewer random measurements which are non-adaptive. The CS acquisition model can be described mathematically by (1) and is shown in Fig.3.

$$Y=\Phi X \qquad (1)$$

where, $x \in R^n$ or C^n is an input signal of length n, Φ

$\in R^{mXn}$ or C^{mXn} an mXn random measurement matrix and is $y \in R^m$ or C^m is the measurement vector of length m. The Input signal and the random measurement matrix are multiplied together to generate compressive measurements. Here, the number of measurements taken are much lesser than the length of input signal, *i.e.*, $m < n$. The size of measurement matrix and hence the number of measurements is proportional to the sparsity of input signal. To further reduce the number of measurements which are necessary for perfect reconstruction, the measurement matrix must be incoherent with basis in which signal has sparse representation.

B. Reconstruction Model

The CS reconstruction model is shown in Fig.3.

The signal x can be represented as a linear combination of columns of or the basis vectors as

the sparse coefficient vector of length n, having fewer Signiant nonzero entries. The original signal can be recovered back from compressive measurements by solving (1), which is an underdetermined system of linear equations and have infinitive number of possible solutions. In such cases, the unique solution can be obtained by posing the reconstruction problem as an `l0-optimization problem given by (3). The `l0-optimization problem searches for asolution having minimum `0-norm subject to the given constraints. This is equivalent to trying all the possibilities to findthe desired solution. Although `l0 is not a proper norm, it is a pseudonorm or quasinorm, which represents the number of non-zero elements of a vector. Searching for a solution of (3) by trying all possible combinations is computationally extensive exercise even for a medium sized problem. Hence, `l0-minimization problem has been declared as NP-hard. Alternates have been proposed in literature, which can obtain a solution similar to the `l0-minimization for the above problem, in near polynomial time. One of the options is to use convex optimization and searching for a solution having minimum `l1-norm, as given by (4). This is considered as a feasible option because solvers available from linear programming can be used for solving the `1-minimization problems in near polynomial time.

The output of CS reconstruction algorithm is an estimate of sparse representation of x, *i.e.*, Os. The estimate of x, *i.e.*, Ox can be obtained from Os by taking its inverse transform.

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II. CS RECONSTRUCTION APPROACHES

CS reconstruction algorithms try to find out the sparse estimation of the original input signal, from compressive measurements, in some suitable basis or frame or dictionary. A lot of research has been done on this aspect of CS, to come up with better performing algorithms. The research driving factors in this area are ability to recover from minimum number of measurements, noise robustness, speed, complexity, performance guarantees, etc. [8]. The CS reconstruction algorithms are mainly classified under six approaches, as shown in Fig.3

This section summarizes the popular algorithms under each approach.

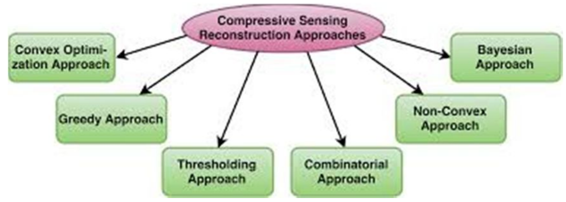

TABLE 3. Comparative summary of CS reconstruction approaches.

Approach	Complexity	Attributes	Pros	Cons
Convex	$\approx O(m^2n^3)$	− global optimization method − minimizes ℓ_1-norm to find solution	− noise robustness − ability to superresolve	− slower, Complex − difficult to implement for problems of larger size
Greedy	−serial version: $O(mnk)$ −parallel version: $O(mn.iter)$	−correlation based step-by-step iterative method	−faster, low complexity and noise robustness −parallel versions has ability to discard wrong entries selected in previous iterations	−prior knowledge of signal sparsity is required − requires more measurements than convex counterparts −convergence issues
Thresholding	$O(mn.iter)$	−uses some nonlinear thresholding criteria to select atoms	−faster and low complexity − ability to add/discard multiple entries per iterations	−Convergence issue with IST −better performance requires adaptive step size which increases complexity
Combinatorial	linear in n	−computes min or median of measurements identified as consisting of a particular I/P sample	−faster and simpler	−requires noiseless and specific pattern in measurements
Non-Convex	same as convex approaches	−minimizes ℓ_p-norm to find solution, where $0 < p < 1$ −global optimization method	− recovers from fewer measurements than ℓ_1 counterpart − functions under weaker RIP − no. of measurements and error decreases with p	−slower, complex − difficult to implement for problems of larger size
Bayesian	$O(nm^2)$	−poses recovery as Bayesian inference problem −applicable for signals belonging to some known probability distribution	−faster and yields more sparser solution −estimates signal parameters without user intervention	−results are prior dependent which is difficult to select −high computational cost

Fig.4. This multiplies light incident from scene with the pseudorandom pattern through DMD array.

III. APPLICATIONS OF COMPRESSIVE SENSING

CS is being a growing field and a wide variety of applications has benefeted from this sensing modality.

A. Single-Pixel Camera

For image acquisition using CS, several imaging architectures have been proposed in literature. One of the early and very famous architecture that demonstrates compressive imaging is the single-pixel camera proposed by Duarte *et al.* in 2008. This consists of a digital micro-mirror devices (DMD) array and the mirrors in this array can be turned on/off using a pseudorandom pattern generated by a pseudorandom sequence generator as shown in Fig.20. The operation up to this stage is equivalent to demodulation stage of RD, refer from DMD array is then collected and focused onto a single photon detector and hence the name `single-pixel camera'. The job of this photodiode is equivalent to the integrator stage RD. The output of photodiode is then sampled by a low rate ADC to generate set of compressive measurements. These
measurements can be easily stored or transmitted. At receiver end, the original scene can be re
constructed using CS reconstruction approach.

B. Radar Imaging Systems

The various types of radar imaging techniques
where CS has been used are synthetic aperture radar (SAR), inverse synthetic aperture radar (ISAR), through the wall imaging radar (TWR) and ground penetrating radar imaging (GPR). In SAR imaging CS has been used to obtain high resolution map of spatial distribution of targets and terrain from much lesser transmitted/received data, simultaneously offering the advantages like resistance to countermeasures and interception.

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C. Communication Systems

The research community has accepted the wider applicability of CS in communication systems. In this section a review of widely used communication systems where CS is being

applied is presented and also highlighted some important aspects of communication systems where CS plays an important role in making these systems efficient.

D. Communication Networks

1) *Wireless Sensor Networks:* The efficient data gathering schemes based on CS has been proposed for wireless sensor networks (WSN) in exploiting raw data compressibility using opportunistic routing. These compressive data gathering schemes offers advantages like robustness, prolonged network lifetime, reduced energy consumption and simple routing scheme, etc. Apart from data gathering, the other aspects of WSNs like routing protocols, channel estimation, multiple access scheme, mitigating the data loss problem during transmission, clone identification, link quality information exchange, data acquisition protocols for reactive WSN and target localization in WSNs has also been looked from the point of view of CS. The various WSNs where CS has been applied are wireless body area networks brain-machine interface and wireless surface electromyography (EMG) for tele-health monitoring; wireless structural health monitoring and wireless cold chain monitoring surveillance; lookup for roadside open wireless access points and environment data gathering protocols for environment reconstruction application for in-depth understanding of physical world. In context to IoT, CS has been applied to address the issues like reduction in energy consumption in handling big data multiuser-detection etc.
2) *Antenna Arrays:* CS has been used to reduce the number of elements and background interference in antenna array to achieve desired beamforming. CS has also been used to optimize the design of tripole arrays and to determine target range and azimuth using random frequency diverse antenna array.
3) *Cognitive Radio (CR) Networks:* CS finds its applicability in CR communication by exploiting the sparsity in spectrum occupancy due to under-utilization of spectrum. CS based AICs have been proposed for efficient wideband spectrum sensing in CRs. The problem of primary user detection in CRs has also been addressed using total variation minimization, modified OMP algorithm, Bayesian framework, blind spectrum detection, cooperative sensing, distributed sensing, adaptive sensing, etc.
4) *UWB Communication:* UWB communication basically makes use of CS architecture called RMPI, for acquisition of UWB signals. The reconstruction of original signal can be done by exploiting its spatial and temporal information. The other issues like, impulse radio detection, echo detection, channel estimation, high precision ranging and non-coherent UWB systems, etc. has also been addressed using CS.

IV. CHALLENGES AND FUTURE SCOPE

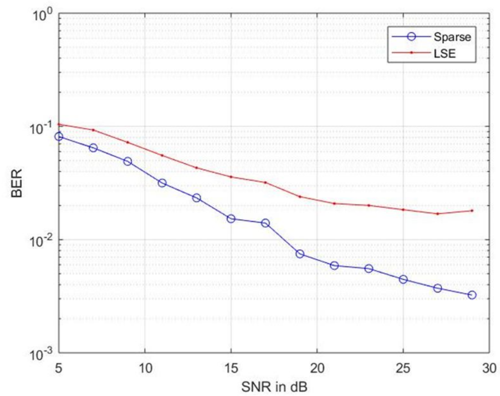
CS has gained a wider acceptance in a shorter time span, as a sampling technique for sampling the signals at their information rate. CS takes the advantage of sparsity or compressibility of the underlying signal to simultaneously sample

and compress the signal. CS has a strong mathematical foundation also. But, the increasing popularity and acceptability of CS faces some challenges. We are highlighting some of the challenges, which also leads to some working directions in the field. There is need for a simple and efficient, universal CS acquisition strategy which is applicable to majority of the signals and also leads to faster acquisition. Similarly, a universal CS reconstruction algorithm, which is faster, robust, less complex and gives guaranteed convergence is needed. Searching a suitable basis, in which signal to be acquired has sparsest possible representation, is itself a tough task. If one can identify the basis in which signal has the sparsest possible representation, then it will help in faithful reconstruction from further reduced CS measurements. So, a system needs to be developed, which can determine the sparsifying basis of signal.

Development of rigorous performance bounds for the issues like minimum number of measurements and reconstruction iterations required for perfect reconstruction, guaranteed convergence, stable recovery, etc., are also workable areas in this field. Also, research is being going on structured CS. The

advantages of this approach are faster acquisition, lower complexity, easier to implement, etc. But the drawbackis that the faithful reconstruction requires more number of measurements. Also, it is difficult to have structured measurement matrices which obey RIP condition. Some proposals of RIPless CS have also been seen in literature, which can be worked further to take advantages of structured measurements in CS.

V. RESULTS



VI. CONCLUSION

Introduction of CS has revolutionized many areas in signal processing, where there were limited scopes. Some of the major contributions are faster MRI, high quality image and video acquisition using single pixel camera, acquisition of UWB signals while drastically reducing the power consumption, etc. This paper has presented a systematical review of CS. Considering its rigorous mathematics, which is sometimes a barrier for many young researchers, we presented a
simpli_ed introduction of CS. For an easy transition from theory with practicality, a summary of CS acquisition techniques and reconstruction approaches has also been presented. The CS acquisition approach may vary from signal to signal. Similarly, the reconstruction approach to be used is also highly signal dependent, which may further need to be modified to suit a particular situation. It will be highly beneficial to have a universal CS acquisition and reconstruction strategy. A review of major application areas where CS is currently being utilized has also been presented.

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