Channel Estimation for Massive MIMO Communication Systems Based on Compressive sensing

Ravikanth Sivangi [1], M. Vinod kumar reddy[2] B. Shanker[3],
[1] Asst. Prof., CVR College of Engineering, ECE Dept, Hyderabad
[2] Asst. Prof., CVR College of Engineering, ECE Dept, Hyderabad
[3] Asst. Prof., CVR College of Engineering, ECE Dept, Hyderabad.

ABSTRACT Massive multiple-input multiple-output (MIMO) is believed to be a key technology to get 1000x data rates in wireless communication systems. Massive MIMO occupies a large number of antennas at the base station (BS) to serve multiple users at the same time. It has appeared as a promising technique to realize high-throughput green wireless communications. Massive MIMO exploits the higher degree of spatial freedom, to extensively improve the capacity and energy efficiency of the system. Thus, massive MIMO systems have been broadly accepted as an important enabling technology for 5th Generation (5G) systems. In massive MIMO systems, a precise acquisition of the channel state information (CSI)is needed for beamforming, signal detection, resource allocation, etc. Yet, having large antennas at the BS, users have to estimate channels linked with hundreds of transmit antennas. Consequently, pilot overhead gets prohibitively high. Hence, realizing the correct channel estimation with the reasonable pilot overhead has become a challenging issue, particularly for frequency division duplex(FDD) in massive MIMO systems. In this paper, by taking advantage of spatial and temporal common sparsity of massive MIMO channels in delay domain, non orthogonal pilot design and channel estimation schemes are proposed under the frame work of structured compressive sensing(SCS) theory that considerably reduces the pilot overheads for massive MIMOFDD systems.

INDEX TERMS Compressive sensing, sparsity, CS acquisition strategies, random demodulator, CS reconstruction algorithms, MIMO, Massive MIMO.

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.

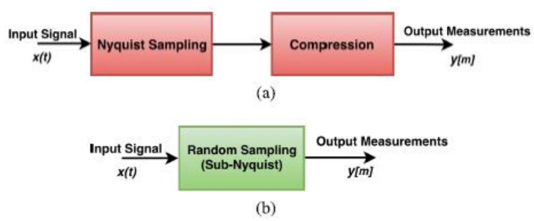


FIGURE 2. A comparision of sampling techniques: (a) traditional sampling, (b) compressive sensing.

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).

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.

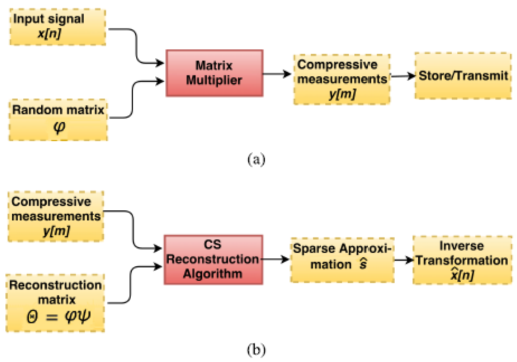


FIGURE 3. CS Model: (a) acquisition model, (b) reconstruction model.

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.

II 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 Є R^n or C^n is an input signal of length n, Φ Є R^{mXn} or C^{mXn} an mXn random measurement matrix and is y Є 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.

II 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.

III. 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.

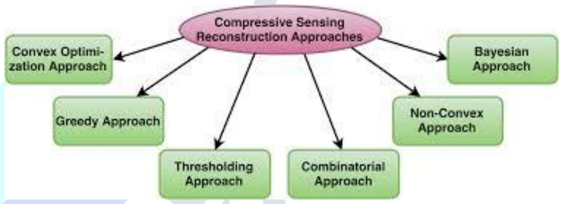


TABLE 3. Comparative summary of CS reconstruction approaches.

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

IV. MASSIVE MIMO

Multiple-input multiple-output (MIMO) systems have multiple antennas at both the transmitter and receiver ends. By addition of multiple antennas, higher degree of freedom in wireless channels (in terms of time and frequency dimensions) can be obtained in order to achieve target of high data rates. For this reason, major performance progress can be attained in terms of system reliability and both spectral and energy efficiency. And also such higher degrees of freedom can be exploited using beamforming given that channel state information is available. There are large number of antenna elements (around tens or even hundreds) deployed at both sides, the transmitter and receiver. It is important to note that the transmit antennas may be distributed or co

located in different applications. Also, the huge number of receive antennas can be acquired by one device or distributed to many dev ices[1,2].Additionally, massive MIMO systems help in minimizing the effects of noise and fast fading, and also intracell interference can be reduced using straight forward detection and linear precoding methods. By appropriately implementing multiuser MIMO(MU-MIMO) in massive MIMO systems, the design of medium access control (MAC) layer can be more simplified by getting rid of complicated scheduling algorithms. One of the major issues in massive MIMO systems is the accurate acquisition of the channel state information (CSI)for beamforming, resource allocation, signal detection, etc. Due to large antennas placed at the BS, the estimation of channels linked with hundreds of transmit antennas is required at users which results in high pilot over head. Hence, the precise channel estimation with the low pilot over head is a challenging task.
CS is being a growing field and a wide variety of applications has benefeted from this sensing modality.

V. Massive MIMO Channel Estimation Based on Compressive Sensing

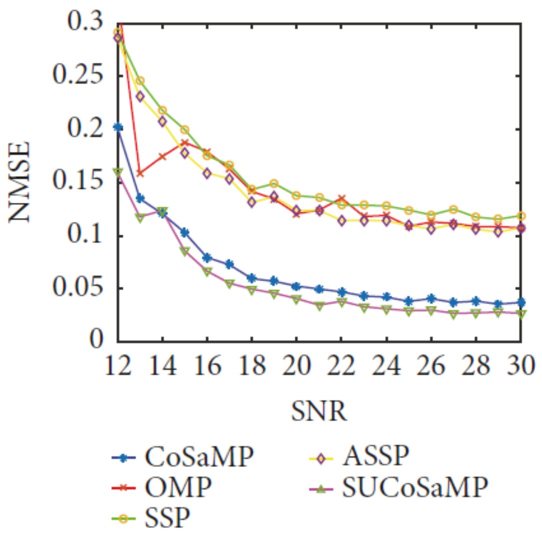
The basic idea presented by CS theory is to recover a signal which is sparse in some domain from extremely small amount of nonadaptive linear measurements by applying convex optimization. In a different opinion, it relates the precise recovery of a sparse vector of high dimension by reducing its dimension. From another point of view, the problem can be considered as calculation of a signal's sparse coefficient with respect to an over complete system. The concept of compressed sensing was primarily applied for random sensing matrices, which allow for a reduced amount of nonadaptive, linear measurements. These days, the idea of compressed sensing has been generally replaced by sparse recovery.
For channel estimation purpose we propose the SUCoSaMP algorithm derived from basic CoSaMP as described in Algorithm1. There will be Ng similar parallel processing required for estimating the massive MIMO channels with Ng sub-antenna groups; i.e., the same algorithm will be working simultaneously with user to estimate channels ofNg subgroups. There are many natural approaches of stopping the algorithm. We follow the following stopping criterion: if$\|vk+1\|2> \|vs-1\|2$, the iteration is stopped [39]. The information of correct sparsity level Sz,m,n is usually not available and also it is practically not possible to have prior knowledge of correct sparsity level, whereas information about sparsity level plays a significant role in compressive sensing problem of solving underdetermined system and it is also required as prior information by most of the CS based algorithms. The proposed SUCoSaMP algorithm does not require prior information of sparsity level because it adaptively acquires the sparsity level and avoids the unrealistic assumption of having prior information of correct sparsity level.

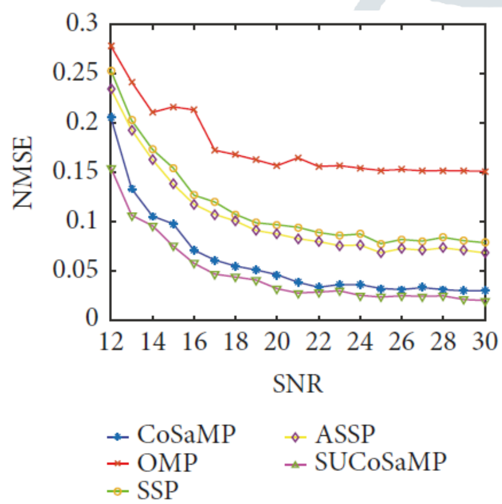
V. CHALLENGES AND FUTURE SCOPE

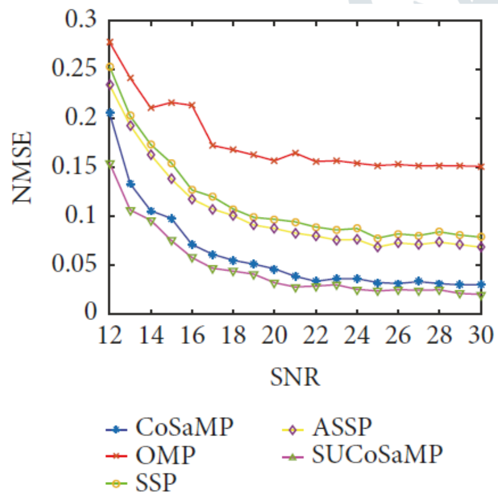
CS has gained a wider acceptance in a shorter time span, as a sampling technique for sampling the signals at their information rate. CS takes the advantage of sparsity or compressibility of the underlying signal to simultaneously sample
and compress the signal. CS has a strong mathematical foundation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

VIII. RESULTS

Simulations have been performed in MATLAB in order to verify the effectiveness of the proposed methods. Mean square error performance of proposed scheme is compared with the conventional OMP, CoSaMP, Structured Subspace Pursuit (SSP), and Adaptive Structured Subspace Pursuit (ASSP) algorithms. Simulation parameters are mentioned in Table 3 for the proposed system. The BS has 1D 1x128 antenna array (M = 128). The system bandwidth and carrier frequency are set to B = 20MHz and f_c = 2GHz, respectively. There are N_g = 8 sub-antenna groups with
16 transmit antennas in each group to ensure the spatial channel sparsity within group. The OFDM subcarriers are set as N = 2048, guard interval is N_G = 16 which could fight the delay spread up to 6.4 μs, and 16QAM modulation is used. The numbers of pilot subcarrier N_p in OFDM
symbol transmitted by each antenna in each antenna group and channel length L are varied over a reasonable range to verify the performance of the proposed system. The pilot positions are uniformly distributed according to (16) and are identical for the entire antennas within one group. The number of multipath channels is randomly chosen and the channel multipath amplitudes and positions follow Rayleigh and random distribution, respectively.







VII. 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 systematically review of CS. Considering its rigorous mathematics, which is sometimes a barrier for many young researchers, we presented a simplified 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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