An adaptive Compressive sensing-based channel estimation for 5G Massive MIMO Systems

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Abstract: Massive multiple-input multiple-output (MIMO) is a key technology in wireless communications to get data rates of 1000 times. Massive MIMO system has very large number of antennas at the base station (BS) operated for servicing many users at the same time. It is a promising technology for realization of high-throughput wireless communications. Massive MIMO exploits the high degree of spatial freedom so that it greatly improves the channel capacity and energy efficiency of the MIMO system. The massive MIMO systems are broadly accepted as a very important establishing technology for 5th Generation (5G) Wireless communication systems. But in massive MIMO systems, an exact determination of the channel state information (CSI)is needed for purpose of effective signal detection, resource allocation and beamforming etc. These systems having a very large number of antennas at the Base Stations, users have to estimate channels which are linked with many numbers of transmit antennas. Due to this, pilot overhead becomes very high. So, realization of the correct channel state information with a minimum pilot overhead will be a challenging issue. Simulation results implemented shows that the proposed algorithm can quickly and accurately determine massive MIMO channel of the unknown channel sparsity and with high computational efficiency when compared with other previous algorithms.

Keywords: 5G; massive MIMO; compressive sensing; sparsity adaptive; a channel estimation

1. INTRODUCTION

Based on Shannon sampling theorem, compressive sensing (CS) is like a breakthrough in signal processing society. It was introduced by Donoho, Candès, Romberg, and Tao in 2004. They also developed mathematical preliminaries of CS. It is generally used for the acquisition of signals which can be sparse (or) compressible. For sparse signals, whole information contained in the signal can be represented only with the help of few significant components, when compared to the total length of the signal. Otherwise the arranged components of a signal which changes rapidly while obeying power law, then also these signals are called compressible signals, refer Fig.1.

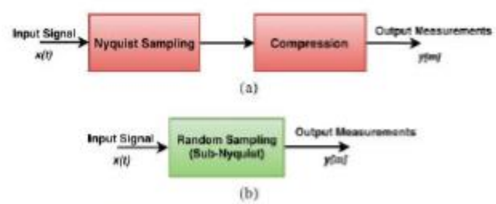


FIGURE 2. A comparision of sampling techniques: (a) traditional sampling, (b) compressive sensing.

A signal which is sparse/compressible can be represented either in its original domain or in some transform domains like Fourier transform, cosine transform, wavelet transform, etc. Massive MIMO (multiple-input multiple-output) is one of the key technologies used in next-generation mobile cellular networks, which has a large number of antennas at its cell base station. MIMO improves greatly the channel capacity and also spectrum utilization [1]. In a massive MIMO system, an exact channel state information (CSI) is crucial so that it effects system signal detection, beamforming, resource allocation and so on. The base station has many antennas so that which greatly deepens the complexity of system data processing. So, in order to make full use of the advantages of massive MIMO technology, the more efficient and low complexity channel estimation algorithms plays a vital role. When compared to conventional MIMO Massive MIMO has various merits. First, MIMO has more number of antennas at the BS so that linear-precoder is used for signal processing such MF or ZF. Second, having large number of antennas at BS increases the system capacity. Third, Low power benefits in the uplink/downlink provides the possibility to make small cells, which can be either micro and pico-cells. The massive multi-input multi-output (MIMO) technology makes the the capacity of the communication system double without increasing the bandwidth and transmission power. Channel estimation is the key challenge in the physical layer of massive MIMO systems. The channel estimation accuracy influences the system performance when the channels are fading. Channel State Information (CSI) is required to utilize the great benefits of MIMO systems [2,3]. However, the exact CSI is not possible to find in real time communication systems[4]. Since the Base station has more number of antennas, the receiver has to estimate more number of channel coefficients, which increases the systems pilot overhead and computational complexity so that it reduces the throughput of the system [5]. This is a challenging issue which has been addressed in [3–6]. Literature [1-3] states that the some massive MIMO channels have sparse characteristics so that effective channel estimation methods are possible. Some classical channel estimation methods like least-square (LS) algorithm , minimum mean-squared error (MMSE) algorithm linear minimum mean square error (LMMSE) and so on are used when channel is not adaptive. But the actual channel has a certain multi-sparseness. Large number of researchers use compressive sensing methods estimate the channel using Pilots. Research shows that compressive sensing based channel estimation achieves better performance based with same number of pilots. Compressive sensing based channel estimation algorithms like orthogonal matching pursuit (OMP) regularization orthogonal matching pursuit (ROMP) and subspace pursuit (SP) etc. are nowadays used. But the above algorithms have to predict the channel sparsity in advance. But the channel sparsity in the actual radio communication systems is generally unknown, so that the above algorithms have some limitation. The sparsity adaptive matching pursuit (SAMP) algorithm determine effectively sparsity-unknown channels, but at the same time the algorithm depends on the iterative steps, which results in the pursuit of high performance and higher computational complexity. Massive MIMO systems are deal with a huge amount of data, and the conventional compressive channel estimation algorithm is difficult to balance between performance estimation and computational complexity. Massive MIMO systems have sub-channels between different transmitting and receiving antenna pairs have the same sparse support set. In adaptive and structured subspace pursuit algorithm (ASSP) for massive MIMO channel estimation has step-by-step approach, achieving sparseness adaptation and the deficiencies have been underestimated, but the computational complexity is very high. This paper estimates sparsity-adaptive channel state information based on the joint sparsity of a massive MIMO channel. If the channel sparsity is unknown in advance, a block based sparse adaptive channel estimation algorithm is proposed, called (BSAMP). The suggested algorithm can be applied to the massive MIMO channel so that the sparse attributes are effectively used for better channel estimation. The key factor here is the threshold limit and determination of the position of the non-zero elements in the support set. The simulation results shows that the proposed method can obtain better channel estimation in performance and with lower complexity provided when the sparsity is unknown.

2 Compressed multipath channel model

When the base station (BS) in MIMO has M transmitting antennas, the end of the transmitter sends orthogonal frequency-division multiplexing (OFDM) signals, where the length of each OFDM signal from each base station antenna is N, and $P(0 < P < N)$ carriers are used as the pilot for channel estimation, and the assumed channel length L. Now the pattern for pilot of the i^{th} transmitting antenna is $p(i)$, $i = 1, 2, ..., M$, where, $p(i) \cap p(j) = \phi$, If $i \neq j$. once channel is transmitted, let $y(p(i))$ be the pilot signal received at the receiver., i = 1, 2, ..., M. Simplifying y(p(i)) as y(i), now the channel can be modelled as

$$y^{(i)} = D^{(i)}F^{(i)}h^{(i)} + m^{(i)}, \; i = 1, 2, L, M \qquad (1)$$

Where, $D^{(i)}$ = diag{p(i)} is the diagonal array with selected pilot patterns, m(i) is a additive white Gaussian Noise with mean value 0 and variance σ^2, F(i) is a P x L sub-matrix of a Fourier coefficients having dimensions of N x N discrete Fourier transform (DFT) matrix pilot line elements and with the first L columns, h(i) = $[h(i)(1), h(i)(2),..., h(i)(L)]^T$ is the impulse response of the channel (CIR) corresponding to the i^{th} antenna. Now, assume that A(i) = D(i)F(i), Then, Equation (1) becomes

$$y^{(i)} = A^{(i)}h^{(i)} + m^{(i)}, \; i = 1, 2, L, M \qquad (2)$$

2.1 SPARSE ADAPTIVE MATCHING PURSUIT ALGORITHM

Solving the channel estimation based on compressive sensing is same as solving the following l_0 norm minimum problem.

$\hat{h}$ = arg min $\|h\|_0$, subject to $\|y\text{-}ah\| \leq \epsilon$

where $\|h\|_0$ is the vector l_0 norm of the vector h for the non-zero elements. Here the impulse response of the channel (h) can be restored. and, spark(A) is the column number in matrix A; however, 2< spark(A) < rank(A) + 1. Since matrix A is the P X L partial Fourier matrix and P < L, then, $\|h\|_0 < ½ (P + 1)$. Since the wireless communication channel is sparseness, its most of the energy is concentrated on a few taps and a small part of the distribution of energy is below the threshold level of noise. The channel length L is much greater than number of taps. So, by full use of the sparse characteristics of the channel, we can use small number of pilot symbols to get the ideal channel estimation, so that spectrum utilization is improved. Based on the above conclusion, the number of non-zero taps in the channel vector does not exceed K, and at least L X K elements are considered as noise. Now, estimate the sparseness and then find out the elements within this range. The difference between adjacent elements is used to select the number of elements for this iteration and sparsity can be estimated. The elements that with the largest backward difference are selected for the support set because they will the carry channel information. When the observation matrix satisfies above conditions, the sparse signal restoration problem is same as solving the convex optimization problem. Let A be the observation matrix and parameter d_k is the minimum value of d which satisfies the following equation,

$$(1 - \delta) \|h\|_2 < \|Ah\|_2 < (1+ \delta)$$

Where, h is the sparse signal for k, if $\delta_k < 1$, the observation matrix A satisfies the kth order RIP. The reconstruction problem becomes following l_1 norm minimum problem.

$\hat{h}$= arg min $\| h\| 1$, subject to $\| y\text{-}Ah \|_2 < \epsilon$

2.2. Sparse Multipath Channel Estimation

Because of the joint sparseness of massive MIMO channel, the channel vector transformed to

$$w = [w1^T, w2^T,..........wL^T]^T$$

where $w_i = [h^{(1)}(i), h^{(2)}(i),..., h^{(M)}(i)]^T$, i = 1, 2, ..., L, the i^{th} sub-block for w. Consider all transmit antennas, the received signal can be written as

$$z = Bw + n$$

Where, B = [B_1, B_2, ..., B_L]; $B_i = [a^{(1)}(i), a^{(2)}(i), ..., a^{(M)}(i)]$, i = 1, 2, ..., L is the ith sub-block of matrix B, $a^{(M)}(i)$ is the i^{th} column of the matrix $A^{(M)}$. If the channel sparsity is unknown then compressed sensing is used to estimate w. Then multiply both sides of above equation by B^H, where B^H is the conjugate transpose of the matrix B.

$$B^Hz = B^H(Bw + n) = (I + B^HB - I)w + B^Hn$$
$$=w + (B^HB - I)w + B^Hn$$

Where, I denote ML x ML unit matrix. Because of the matrix B, there is no perfect orthogonality condition. $B^HB - I$ represents the nonzero matrix with a small numerical value. The observed matrix is

$$n' = (B^HB - I)\, w + B^Hn,$$

Then, above Equation becomes

$$B^Hz = w + n'$$

During iteration, Let R represents an ML x 1 vector R, where

$$R = |B^Hr|$$

Where, r represents iterative residuals, with initial value z, and | | represents the absolute value of the elements in $B^H r$. Now, the vector T can be assumed as the sum of the squares of each set of M elements in the vector. Because of the gain coefficient of the channel tap is higher than the noise amplitude, so that for every iteration of the algorithm, The element amplitudes Ts produces a larger rate of change; and the element before this position shall carry the information of the channel . So, finding the maximum backward difference between adjacent elements find out the number of elements selected in this iteration, and the elements before this position are considered as the support set as carry information channel . In order to improve the accuracy of the selected eleme nts, the regularization process based on convex optimization must be adopted. The above analysis guarantees that the sparse estimation of BSAMP algorithm first estimates the sparsity upper limit by setting the threshold. Sparseness is further estimated while finding the maximum difference location in this range for separation of channel taps and noise. Compared to other compression based algorithms, the effected factors associated with additive white Gaussian white noise are $B^H n$. The BSAMP algorithm will considers $B^H n$ but at the same time it considers the energy dispersion due to the non-orthogonality of the observation matrix $(B^H B - I)\,w$. The proposed BSAMP algorithm use regularization method to filter the elements in the support set for secondary screening, which they can improves the accuracy of the support set. Therefore, the BSAMP algorithm has better estimation performance when compared to other existing algorithms. The massive MIMO system will recover the maximum channel dimension, and the sub-channel has combined sparseness. The BSAMP algorithm uses advantage of channel block sparse features, so that iterations are reduced. At the same time there because of multi element-selected support sets in each iteration, I t avoids the iterative step-size so that BSAMP algorithm has low computational complexity.

Massive MIMO Channel Estimation Based on Compressive Sensing

From the CS theory a signal which is sparse in some domain can be recovered from extremely small amount of linear measurements by using convex optimization. That is it recover precise sparse vector of higher dimension by lowering to its dimension. In another view the problem can be considered as calculation of a signal's sparse coefficient with respect to an underestimate system. Initially the concepts of compressive sensing methods were applied to random sensing matrices, which are nonadaptive and linear measurements. But, these days, the idea of compressive sensing is being generally replaced by sparse recovery. It could be seen that $\tilde{h}_{z,n}$ demonstrates structured sparsity in delay domain where $\tilde{h}_{z,n}$ is $S_{z,m,n}$-sparse vector due to

$$P_{z,m,n} = \mathrm{supp}\, \{\tilde{h}_{z,n}\} = \{l : h_{z,n}[l] > 0\}$$

with $1 \leq l \leq L$ where $S_{z,m,n} = |P_{z,m,n}|_C$ fulfilling $S_{z,m,n} \ll L$. And due to spatial sparsity we have the following. $P_{z,1,n} = P_{z,2,n} = \cdots = P_{z,M,n}$

The required small correlation A_n based on CS theory will be obtained so that the desired sparse recovery is guaranteed. It will be further shown that any two columns of A_n have good cross correlation between them. The proposed pilot design is simple to use and also easy in terms of compatibility with current wireless networks. For K adjacent OFDM symbols with identical pattern of pilots,

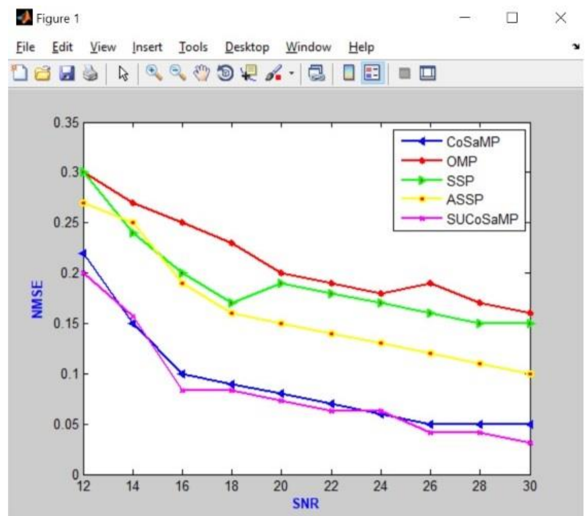
$$Y_n = A_n H_n + W_n$$

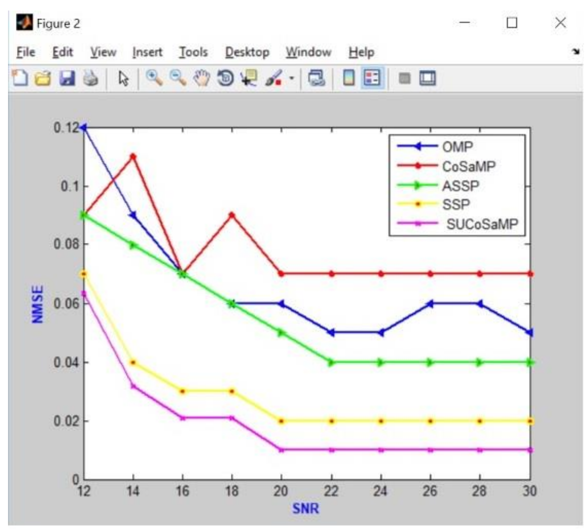
where $Y_n = [y_{z,n}, y_{z+1,n}, \ldots, y_{z+K-1,n}] C^{N_p \times K}$.

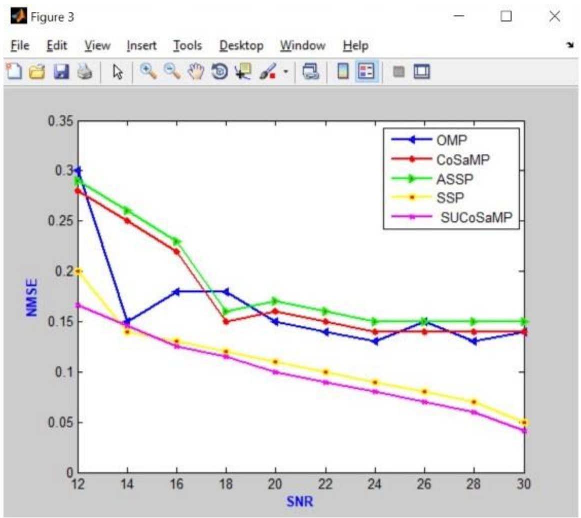
There are many algorithms that can find the solution for the problem. The greedy algorithm is a orthogonal matching pursuit (OMP). For estimation of channel we propose the SUCoSaMP algorithm derived from basic CoSaMP. There are N_g sof same parallel processing are required for estimating the massive MIMO channels. There are many existing methods for stopping the algorithm. When the following stopping criterion satisfied, if $\|v_{k+1}\|_2 > \|v_{s-1}\|_2$, the iteration will be stopped. The information of exact sparsity level $S_{z,m,n}$ generally not available and it also not practically possible to have prior knowledge of exact sparsity. The information about sparsity level plays a significant role in compressive sensing problem while solving underdetermined systems. The suggested SUCoSaM algorithm does not require prior information about sparsity level since it adaptively gets the sparsity level. But the suggested SUCoSaMP algorithm works in the same way as the CoSaMP algorithm works. The CoSaMP algorithm is based on basic OMP. The SUCoSaMP algorithm has some other ideas so that it guarantees that OMP and CoSaMP does not provide and it increase speed of the algorithm when compared to OMP. The advantage of SUCoSaMP over OMP, CoSaMP, and other basic subspace pursuit (SP) algorithms in that it does not require the prior information of sparsity level btg66ecause it is an unrealistic assumption. But there are two minor differences between SUCoSaMP and CoSaMP. First, the SUCoSaMP algorithm estimates the channels; Second, SUCoSaMP attains adaptively the level of sparsity. The CoSaMP algorithms esimates the sparse vector without using the structured sparsity level. The suggested method stops the iteration with sparsity level of constant. There are two different types of iterations in SUCoSaMP, one on k and one on s, and finally the iterations on s are stopped when $\|v_{k+1}\|_2 > \|v_{s-1}\|_2$.

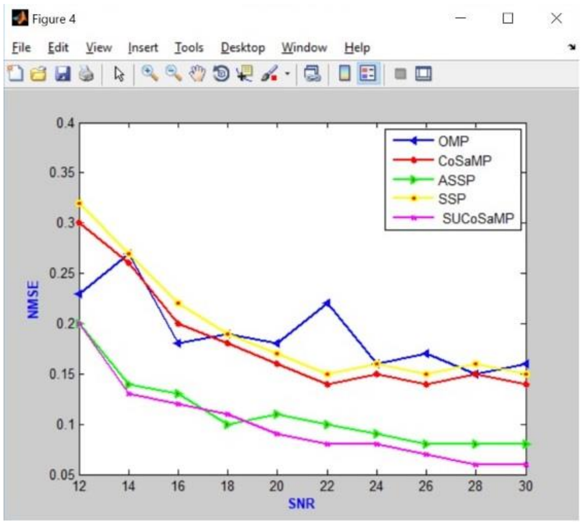
SIMULATION RESULTS

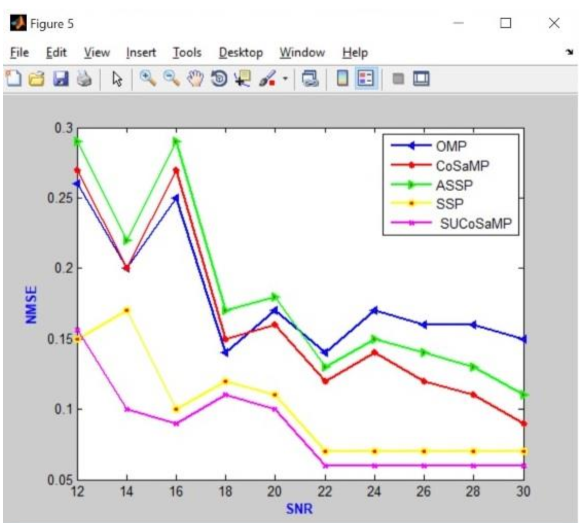
Simulations were performed in MATLAB simulator in order to verify the complexity of the suggested methods. MSE (Mean square Error) performance of suggested method is compared with existing OMP, CoSaMP, Structured Subspace Pursuit (SSP), and Adaptive Structured Subspace Pursuit (ASSP) algorithms. The Base station has 1x128 antenna array with M=128. The proposed system has bandwidth and carrier frequency are B =20MHz and f_c = 2GHz, respectively. We consider N_g = 8 sub-antenna groups with 16 transmit antennas in each group. The OFDM subcarriers are taken as N = 2048, and guard interval is N_G = 16 and delay spread is 6.4 μs, and modulation taken is 16QAM modulation. The pilot subcarriers are N_p in OFDM symbol which are from each transmitted antenna of length L. The multipath channels are randomly chosen in which channel multipath amplitudes and positions follow Rayleigh and random distribution, respectively. Figure 1 shows the Mean Square Error (MSE) performance of the suggested method SUCoSaMP algorithm for different values of N_p versus signal to noise ratio (SNR). The performance of SUCoSaMP is compared with the existing algorithms like OMP and CoSaMP and with SSP and ASSP. From the simulation results it is shown that the estimation of channel performance of existing algorithms is improved by increasing number of pilot subcarriers N_p. The proposed SUCoSaMP algorithm performs in a better way than all other algorithms since the SUCoSaMP allows maximum advantage of sparsity of massive MIMO channels. Since the sparsity level of Massive MIMO prior information is available in a realistic wireless communications, the suggested SUCoSaMP algorithm shows the better advantage over other all existing algorithms.











CONCLUSIONS

In this paper we propose a novel nonorthogonal pilot-based method on Compressive sensing algorithm called SUCoSaMP for estimating channels in massive MIMO systems. From the simulation results it is shown that the pilot overhead is is reduced in MIMO systems. With the benefits of spatial and temporal sparsity, proposed nonorthogonal pilot design method and estimation of channel schemes for the massive MIMO channels in the delay domain, shows that there is reduction in pilot overhead. Further, the proposed methods can be extended to multi cells.

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