A novel Channel Estimation for Massive MIMO Systems using Sparse compressive sensing

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Abstract: Aiming at a massive multi-input multi-output (MIMO) system with unknown channel path number, a sparse adaptive compressed sensing channel estimation algorithm is proposed, which is the block sparsity adaptive matching pursuit (BSAMP) algorithm. Based on the joint sparsity of sub channels in massive MIMO systems, the initial set of support elements can be quickly and selectively selected by setting the threshold and finding the maximum backward difference position. At the same time, the energy dispersal caused by the non orthogonality of the observation matrix is considered, and the estimation performance of the algorithm is improved. The regularization of the elements secondary screening is deployed, in order to improve the stability of the algorithm. Simulation results show that the proposed algorithm can quickly and accurately recover massive MIMO channel state information with unknown channel sparsity and high computational efficiency compared with other algorithms.

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

Introduction

Massive MIMO (multiple-input multiple-output) technology is one of the key technologies of next-generation mobile cellular networks, which can form a massive antenna array by providing a large number of antennas at the cell base station. It will greatly improve the channel capacity and spectrum utilization and has become a hotspot in the field of wireless communications in recent years [1]. In a massive MIMO system, precise channel state information (CSI) is critical, which is directly related to the system signal detection, beam forming, resource allocation and so on. The number of base station antennas in massive MIMO systems has reached hundreds of thousands, which greatly deepens the complexity of system data processing. Therefore, in order to make full use of the potential advantages of massive MIMO technology, the more efficient and low complexity channel estimation algorithms are worthy of further study. Massive MIMO has various merits over the conventional MIMO. First, it uses a large number of antennas at the BS due to which the simplest coherent-combiner and linear-precoder can be used for signal processing such MF or ZF. Second, increasing the number of antennas increases the system capacity substantially using the channel-reciprocity features and without increasing feedback-overhead. Third, the reduced power benefits in the uplink/downlink (UL/DL) provide the feasibility to shrink the cell-size, which can be used in micro and Pico-cells.

In massive MIMO systems, accurate Channel State Information (CSI) is required to utilize the full potential of MIMO systems. However, such accurate CSI is not available in real communication environment [4]. With the increasing number of antennas, the receiver has to estimate more channel coefficients, which effectively increases the pilot overhead, computational complexity and reduces the overall throughput of the system. This is a challenging issue which has been addressed in

[3–6]. Massive MIMO channel has sparse characteristics which can be utilized for computationally-efficient channel estimation. Classical channel estimation methods include least-square (LS) algorithm, minimum mean-squared error (MMSE) algorithm and linear minimum mean square error (LMMSE) and so on. The actual radio channel has certain multi-sparseness .In recent years, a large number of researchers applied compressive sensing to the pilot-aided channel estimation.Research shows that compressed channel estimation achieves better performance based on the same number of pilots in sparse channels.

2. Sparse Multipath Channel Model

In a base station (BS) equipped with M transmitting antenna MIMO systems, the transmitting end sends orthogonal frequency-division multiplexing (OFDM) signals, and the length of each OFDM signal transmitted by each antenna is N, where

$P(0 < P < N)$ carriers are selected as the pilot for channel estimation, and the channel length L. The pilot pattern of the ith transmit antenna is $p(i)$, I = 1, 2, ..., M, where, $p(i) \cap p(j) = \Phi$, If $i \neq j$. After the channel is transmitted, the receiving end receives the pilot signal corresponding to each antenna as $\boldsymbol{y}(p(i))$, i = 1, 2, ..., M. Abbreviate $\boldsymbol{y}(p(i))$ as $\boldsymbol{y(i)}$, the basic channel model can be expressed as:

$$\boldsymbol{y}(\mathbf{i}) = \boldsymbol{D}(\boldsymbol{i})\boldsymbol{F}(\boldsymbol{i})\boldsymbol{h}(\boldsymbol{i}) + \boldsymbol{m}(\boldsymbol{i}),\ i = 1, 2, L, M \quad (1)$$

among them, $\boldsymbol{D(i)}$ = diag$\{\boldsymbol{p}(i)\}$ is a diagonal array of selected pilot patterns, $\boldsymbol{m(i)}$ is a Gaussian White

Noise with mean 0 and variance σ^2, $\boldsymbol{F(i)}$ is a $P \times L$ sub-matrix of a Fourier, corresponding to the

dimensions $N \times N$ discrete Fourier transform (DFT) matrix pilot line elements and the first L

columns, $\boldsymbol{h(i)} = [h\boldsymbol{(i)}(1), h\boldsymbol{(i)}(2),..., h\boldsymbol{(i)}(L)]^{T}$ is the channel impulse response (CIR) corresponding to the ith antenna. Make $\boldsymbol{A(i)} = \boldsymbol{D(i)F(i)}$, Then, Equation (1) can be further expressed as:

$$\boldsymbol{y(i)} = \boldsymbol{A(i)h(i)} + \boldsymbol{m(i)},\ i = 1, 2, L, M \quad (2)$$

3. Sparse Adaptive Matching Pursuit Algorithm

3.1. Sparseness Estimation

Using compressed sensing to solve channel estimation can be equivalent to solving the following l_0 norm minimum problem.

$$\hat{\boldsymbol{h}} = \arg\min \|\boldsymbol{h}\|0, \text{ subject to } \|\boldsymbol{y} - \boldsymbol{Ah}\|2 \leq \varepsilon \quad (3)$$

among them $\|h\|_0$ is the vector l_0 norm of the vector $\boldsymbol{h}$ for the number of non-zero elements.

only the channel impulse response $(\boldsymbol{h})$ can be restored. Among them, spark ($\boldsymbol{A}$) is the least

Linearly related column number in matrix .Because of the sparseness of the impulse response of the wireless communication channel, most of the energy is concentrated on a few taps while a small part of the energy distribution is below the noise threshold. The number of non-zero taps is much smaller than the channel length L. Making full use of the sparse characteristics of the channel, we can use fewer pilot symbols to get the ideal channel estimation effect, so as to improve the spectrum utilization. An appropriate amount of pilot overhead satisfies Equation (5), so

$$K = \begin{cases} P/2, & P \text{ is even} \\ (P+1)/2, & P \text{ is odd} \end{cases} \quad (5)$$

Based on the above analysis, the number of non-zero taps in the channel vector does not exceed K, and at least $L - K$ elements can be regarded as noise. Therefore, we first estimate the sparseness and then select the elements within this range. At higher signal-to-noise ratios, since the gain coefficients of the channel taps are higher than the noise amplitudes, the restored vector elements are arranged in descending order. The difference between adjacent elements is then used to determine the number of elements selected for this iteration and to further estimate the sparsity. The elements that precede the largest backward difference are selected for the support set because they may carry channel information.

When the observation matrix satisfies certain conditions, the sparse signal restoration problem can be equivalent to the following convex optimization problem. Define the observation matrix $\boldsymbol{A}$,the RIP parameter δk is the minimum value δ that satisfies Equation

$$(1 - \delta)\|\boldsymbol{h}\|\mathbf{2} \leq \|\boldsymbol{Ah}\|\mathbf{2} \leq (1 + \delta)\|\boldsymbol{h}\|\mathbf{2} \quad (6)$$

When matrix RIP parameters $\delta k < \sqrt{\mathbf{2}}-1$, the reconstruction problem can be transformed into the following l_1 norm minimum problem.

$$\hat{\boldsymbol{h}} = \arg\min \|\boldsymbol{h}\|_{\mathbf{1}}, \text{ subject to } \|\boldsymbol{y} - \boldsymbol{Ah}\|\mathbf{2} \leq \varepsilon \quad (7)$$

3.2. Sparse Multipath Channel Estimation

Aiming at the joint sparseness presented by the massive MIMO channel, the transformed

channel vector is defined as $\boldsymbol{w} = [\boldsymbol{w}1^{T}, \boldsymbol{w}2^{T},..., \boldsymbol{w}L^{T}]$T, where $\boldsymbol{w}i = [h(1)(i), h(2)(i),..., h(M)(i)]^{T}$, i = 1, 2, ..., L, the i sub-block for $\boldsymbol{w}$. At this point, the non-zero elements in the converted channel vector will be concentrated. Correspondingly, the received pilot signal is warped $\boldsymbol{z} = [\boldsymbol{z}1^{T}, \boldsymbol{z}2^{T}... \boldsymbol{z}p^{T}]^{T}$. Among them, $\boldsymbol{z}i = [y(1)(i), y(2)(i), ..., y(M)(i)]$T, i = 1, 2, ..., P. Do the same for noise, $\boldsymbol{n} = [\boldsymbol{n}1^{T}, \boldsymbol{n}2^{T}, ..., \boldsymbol{n}P^{T}]$T, where $\boldsymbol{n}i = [m(1)(i), m(2)(i), ..., m(M)(i)]^{T}$,

i = 1, 2... P. Considering all transmit antennas, the received signal can be expressed as:

$$\boldsymbol{z} = \boldsymbol{Bw} + \boldsymbol{n} \quad (8)$$

among them, $\boldsymbol{B} = [\boldsymbol{B}1, \boldsymbol{B}2, ..., \boldsymbol{B}\mathrm{L}]$; $\boldsymbol{B}i = [a^{(1)}(i), a^{(2)}(i), ..., a^{(M)(}i)]$, i = 1, 2, ..., L is the ith sub-block of matrix $\boldsymbol{B}$, $a^{(M)(}i)$ is the ith column of the matrix $\boldsymbol{A}^{(M)}$. In the case of unknown channel sparsity, the compressed sensing is used to estimate $\boldsymbol{w}$ in Equation (8), so multiply both sides of equation (8) simultaneously by $\boldsymbol{B}$H, where $\boldsymbol{B}$H is the conjugate transpose of the matrix $\boldsymbol{B}$.

$$\boldsymbol{B}^H\boldsymbol{z} = \mathbf{B}^H(\boldsymbol{Bw} + \boldsymbol{n}) = (\boldsymbol{I} + \boldsymbol{B}^H\boldsymbol{B} - \boldsymbol{I})\boldsymbol{w} + \boldsymbol{B}^H\boldsymbol{n}$$

$$= \boldsymbol{w} + (\boldsymbol{B}^H\boldsymbol{B} - \boldsymbol{I})\boldsymbol{w} + \boldsymbol{B}^H\boldsymbol{n} \qquad (9)$$

among them, $\boldsymbol{I}$ denote $ML \times ML$ unit matrix. Due to the matrix $\boldsymbol{B}$, there is no strict orthogonality; therefore, $\boldsymbol{B}$H$\boldsymbol{B}$ – $\boldsymbol{I}$ denote a nonzero matrix with a small elemental value. Consider the dispersion of energy caused by the non-orthogonality of the observed matrix $\boldsymbol{n}' = (\mathbf{B}\mathrm{H}\boldsymbol{B} - \boldsymbol{I})\boldsymbol{w} + \mathbf{B}\mathrm{H}\boldsymbol{n}$, Then,

Equation (9) can be expressed as:

$$\boldsymbol{B}^H\boldsymbol{z} = \boldsymbol{w} + \boldsymbol{n}' \qquad (10)$$

During iteration, define an $ML \times 1$ vector $\boldsymbol{R}$.

$$\boldsymbol{R} = |\mathbf{B}^H\boldsymbol{r}| \qquad (11)$$

among them, $\boldsymbol{r}$ denotes iterative residuals, its initial value is $\boldsymbol{z}$, |.| represents the absolute value of the elements in $\boldsymbol{B}^H\boldsymbol{r}$. Now, define the element in vector $\boldsymbol{T}$ as the sum of the squares of each set of M elements in the vector $\boldsymbol{R}$

$$\boldsymbol{T}(j) = \Sigma j \times M\ |R(i)|2$$

$$(j-1)\times M+1\ ,$$

$$i = 1, 2, \ldots ML;\ j = 1, 2, \ldots, L$$

According to the analysis in Section 3.1 the upper limit of channel sparsity is K. After the first iteration, the last L-K elements in $\boldsymbol{T}$s are only generated by $\boldsymbol{n}'$ inSo the energy of the next L-K elements is set as the threshold f. The non-zero tap energy in the channel is greater than the threshold f. So in $\boldsymbol{T}$s, only elements above this threshold are likely to be included in the support set.

At higher signal-to-noise ratios, since the gain coefficient of the channel tap is higher than the noise amplitude, at each iteration of the algorithm, $\boldsymbol{T}$s of the element amplitude produces a larger

rate of change; then the element before this position has to carry channel information. Therefore, calculating the maximum backward difference between adjacent elements determines the number of elements selected in this iteration, and the elements before this position are selected for the support set because they may carry channel information. In order to further improve the accuracy of the selected elements, the regularization process based on convex optimization is adopted to ensure that the selected element energy is larger than the energy of the unselected elements, and the noise is filtered out to support the set.

4. Simulation Results

The MATLAB simulator is used for the analysis.

Table 1 mentioned the main simulation setup parameters for the proposed system. In the simulation, the system has 500 transmit antennas, using 64QAM modulation and low-density parity-check (LDPC) coding (coding efficiency 5/8). Each transmit antenna sends an OFDM signal with a signal length N of 256, with a cyclic prefix length of 64. The OFDM signals transmitted by each transmitting antenna have 16 pilot symbols, and all the algorithms use the same pilot distribution method. The pilot positions are randomly distributed and the pilots of different antennas are orthogonal to each other. The channel length L is 60, and the number of channel multipath is a random integer. The multipath amplitude follows the Rayleigh distribution, and the multipath positions follow a random distribution.

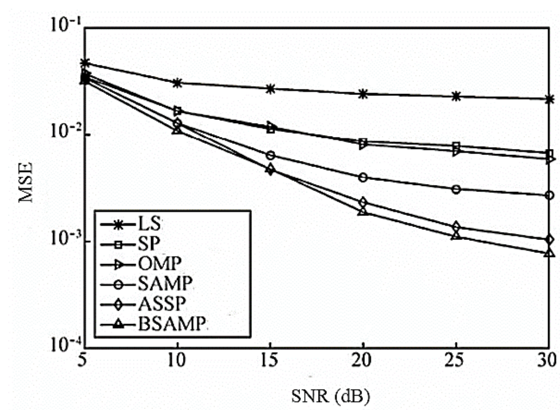

Figure 1. Comparison of mean square error of each algorithm under different signal to noise ratios (SNRs). MSE: mean square error; LS: least-square; SP: subspace pursuit; OMP: orthogonal matching pursuit; SAMP: sparsity adaptive matching pursuit; ASSP: adaptive and structured subspace pursuit; BSAMP: block sparsity adaptive matching pursuit

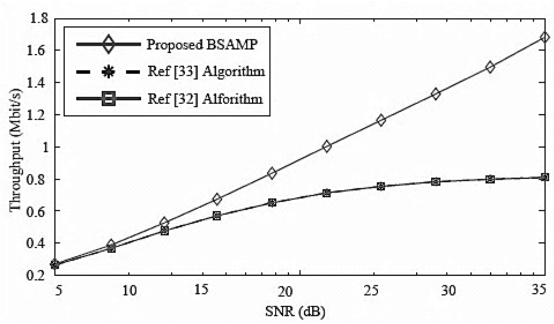

Figure 2. Throughput comparison of each algorithm with increasing SNR.

5. CONCLUSION

This paper proposes a BSAMP algorithm with adaptive sparsity-based on the joint sparsity of sub-channels in massive MIMO systems. The algorithm chooses the support elements as the first choice by setting the threshold and finding the maximum backward difference position. The element is secondarily selected by regularization to improve the accuracy of the selected elements. The MSE, BER and throughput analysis is performed against the SNR and number of pilots. The proposed BSAMP algorithm is compared with LS, OMP, SP, SAMP, ASSP algorithms, and the corresponding system parameters are analyzed for performance evaluations. The algorithm complexity analysis was also performed, which clearly estimated that the proposed BSAMP algorithm has a 0.01284 s average runtime, which is much smaller than the other algorithms such as the average runtime of SAMP algorithm, which is 93.3930 s and the ASSP algorithm which has an average runtime of 15.3610 s. With such a computationally-efficient behavior, the proposed BSAMP algorithm provides efficient sparse channel estimation capability for 5G massive MIMO systems which also enables us to deploy it in practical usage scenarios. Theoretical analysis and simulation results show that the BSAMP algorithm has good channel estimation performance, high throughput and low computational complexity as compared to other algorithms. This research work can further be extended by incorporating the proposed BSAMP algorithm in TDD, FDD Massive MIMO for Energy Efficiency Analysis versus different performance metrics such as the distance between the BS and mobile users, antenna element spacing and hardware impairments.

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