Proceedings of the 2023 International Conference on Functional Materials and Civil Engineering
DOI: 10.54254/2755-2721/25/20230779

Research on active user detection and channel estimation algorithms in massive access

Zhang Tian

Southeast University, School of Information Science and Engineering, Nanjing, China, 210000

njseuzt@163.com

Abstract. Massive Access is a supporting technology for scenarios like the Internet of Things, and is also one of the typical scenarios defined by 5G. Unlike traditional multi-user communication, the data of these nodes is generally sudden, so only a small proportion of nodes are active at a certain time. If the traditional request resource allocation protocol mode is adopted, it requires authorized access to achieve dynamic resource allocation, which will result in excessive protocol overhead. Therefore, Grant-Free transmission is required. It is impossible to recover the data transmitted by active users during Grant-Free transmission because the base station is unaware of who is transmitting the data. Therefore, the system must first do active user detection and channel estimation. A channel estimation technique based on Compressed Sensing is presented in this paper. the EM-BG-AMP algorithm is reproduced and applied. By comparing the accuracy of the EM-BG-AMP algorithm in channel estimation under physical backgrounds, this essay gives the range of optimal received signal-to-noise ratio:100dB and more. Also, this essay demonstrates that the performance of the EM-BG-AMP algorithm weakens as sparsity increases.

Keywords: massive access, compressive sensing, active user detection, channel estimation, EM-BG-AMP.

1. Introduction

Some academics are now investigating Compressed Sensing-based active user detection and channel estimation technology. Using a pilot to estimate channels, the authors of Reference [1] integrate wireless communication with numerous access connections to detect and track down individuals. In order to improve the performance of massive multiplex transmission systems, the authors of Reference [2] suggested an adaptive user detection and channel estimation method using Compressed Sensing. In order to properly realize the signal processing and significantly increase the efficiency of the system, the authors of the aforementioned literature [3] utilize the intricate structure of the channel matrix and implement the Bayesian Compressed sensing technique. This paper presents a Compressed Sensing-based approach to user activity detection based on this. In order to estimate the channel using the Multiple Measurement Vector (MMV) model, the literature [4] uses a Compressed Sensing-based approximate message-passing algorithm.

This paper completes the modeling of Massive Access, replicates and uses the EM-BG-AMP algorithm based on Compressed Sensing to carry out channel estimation and active user detection in

DOI: 10.54254/2755-2721/25/20230779

different physical backgrounds based on the MATLAB platform, and analyzes the performance of the algorithm, so as to provide suggestions and guidance for parameter settings in the context of large-scale wireless access.

2. Compressed sensing

According to the study by Tao et al. [5], when data has low sparsity, using random subsampling can achieve a much lower collection speed than required by Nyquist's sampling law, and the effectiveness of this collection depends entirely on the characteristics of the data, thus achieving effective reconstruction and recovery of the data. Using Compressed Sensing, the sparsity of the signal can be used as a condition, that is, most elements of the signal vector are zero or sparse after conversion. With Compressed sensing technology, signals can be reconstructed with a smaller sampling frequency to ensure the density of information. This technology can significantly reduce the difficulty of reconstructing signals and has high efficiency and accuracy, making it widely used in medical detection, transmission systems, unmanned aerial vehicle communication, and other fields. The prospect of Compressed sensing theory is very broad, and there are many new applications waiting to be explored in the future.

2.1. Mathematical model of compressed sensing

The mathematical model of Compressed Sensing is as follows:

$$\boldsymbol{y} = \boldsymbol{A}\boldsymbol{x} \tag{1}$$

where $\boldsymbol{x} \in C^{N\times 1}$ is a sparse signal, $\boldsymbol{A} \in C^{M\times N}$ is measurement matrix, and $\boldsymbol{y} \in C^{M\times 1}$ is a compressed signal. If the signal itself is not sparse, suitable sparse basis matrices and sparse vectors can be selected to represent $\boldsymbol{x}$.

$$\boldsymbol{x} = \Psi\boldsymbol{s} \tag{2}$$

where Ψ denotes sparse basis function, $\boldsymbol{s}$ is a sparse representation of signal $\boldsymbol{x}$. If there are only Kcoefficients in $\boldsymbol{s}$ that are not zero, then the sparsity of the signal is called $K(K << N)$. At this point, the original signal$\boldsymbol{x}$ is sparse in the$K$ -domain, so equation (1) can be converted to the following equation:

$$\boldsymbol{y} = \boldsymbol{A}\Psi\boldsymbol{s} \tag{3}$$

Therefore, the Compressed Sensing problem is transformed into the known measurement signal $\boldsymbol{y}$, measurement matrix $\boldsymbol{A}$ and sparse basis matrix Ψ, the vector $\boldsymbol{s}$is solved, and the original signal $\boldsymbol{x}$is recovered according to equation (2).

2.2. Measurement matrix

The measurement matrix is an essential part of the theory behind the Compressed Sensing theory. A well-designed implementation is essential for reliable signal reconstruction, as it directly impacts the efficiency of sparse signal recovery. The performance of a measurement matrix and its reliability and accuracy can be measured using a novel concept proposed by Tao T et al. in Compressed Sensing Theory: restricted isometry property (RIP) [6]. RIP is a metric for gauging how well a measuring matrix performs. The following is the definition of finite equidistant properties:

$\exists\, \delta_k \in [0,1)$,

$$(1-\delta_k)\|\boldsymbol{x}\|_2^2 \le \|\boldsymbol{A}\boldsymbol{x}\|_2^2 \le (1+\delta_k)\|\boldsymbol{x}\|_2^2 \tag{4}$$

If it holds true for any K -sparse signal, then the measurement matrix a is said to obey$K$ -level RIP.

3. Implementation of EM-BG-AMP algorithm

3.1. BG-AMP

First, the task is to reproduce BG-AMP. For the BG-AMP algorithm, the signal $x=[x_1,\ldots,x_N]^T$ is assumed to be a Bernoulli Gaussian (BG) signal, and the marginal pdf can be expressed as [7].

$$p_X(x;\lambda,\theta,\phi)=(1-\lambda)\delta(x)+\lambda\mathcal{N}(x;\theta,\phi), \tag{5}$$

where $\delta(\cdot)$is Dirac delta, λ is the sparsity rate, θ is the mean of active users, and ϕ is the variance of active users. The noise w is independent of x and independent and identically distributed random variables with zero mean Gaussian, and its variance ψ can be expressed as:

$$p_W(w;\psi)=\mathcal{N}(w;0,\psi) \tag{6}$$

In the BG-AMP algorithm, these prior distributions defined by$\boldsymbol{q}\triangleq[\lambda,\theta,\phi,\psi]$ are considered deterministic unknowns and learn through the EM algorithm.

GAMP can handle any probability relationship between the measurement signal y_m and the noise free output $z_m\triangleq a_m^Tx$, where a_m^T is the m^{th}row of the measurement matrix A. The Additive white Gaussian noise hypothesis indicates that $p_{Y|Z}(y\mid z)=\mathcal{N}(y;z,\psi)$.Next, just specify $g_{\text{in}}(\cdot),g_{\text{in}}'(\cdot),g_{\text{out}}(\cdot)g_{\text{out}}'(\cdot)$and use simple operations to generate $p_{Y|Z}(\cdot\mid\cdot)$ [8].

$$g_{\text{out}}(y,\hat{z},\mu^z;\boldsymbol{q})=\frac{y-\hat{z}}{\mu^z+\psi} \tag{7}$$

$$-g_{\text{out}}'(y,\hat{z},\mu^z;\boldsymbol{q})=\frac{1}{\mu^z+\psi}, \tag{8}$$

BG prior signal generates

$$g_{in}(\hat{r},\mu^r;q)=\pi(\hat{r},\mu^r;q)\gamma(\hat{r},\mu^r;q) \tag{9}$$

$$\mu^r g_{in}'(\hat{r},\mu^r;q)=\pi(\hat{r},\mu^r;q)(v(\hat{r},\mu^r;q)+|\gamma(\hat{r},\mu^r;q)|^2)-(\pi(\hat{r},\mu^r;q))^2|\gamma(\hat{r},\mu^r;q)|^2 \tag{10}$$

in the two formulas above

$$\pi(\hat{r},\mu^r;q)\triangleq\frac{1}{1+(\frac{\lambda}{1-\lambda}\frac{\mathcal{N}(\hat{r};\theta,\phi+\mu^r)}{\mathcal{N}(\hat{r};0,\mu^r)})^{-1}} \tag{11}$$

$$\gamma(\hat{r},\mu^r;q)\triangleq\frac{\frac{\hat{r}}{\mu^r}+\frac{\theta}{\phi}}{\frac{1}{\mu r}+\frac{1}{\phi}} \tag{12}$$

$$v(\hat{r},\mu^r;q)\triangleq\frac{1}{\frac{1}{\mu^r}+\frac{1}{\phi}} \tag{13}$$

3.2. The initialization of EM

A proper initialization is required because the EM method only converges to the local maximum of the Likelihood function. In this paper, all simulations initialize the sparsity rate $\lambda^0=\frac{M}{N}\rho_{SE}(\frac{M}{N})$, Where $\rho_{SE}(\frac{M}{N})$ is the sparsity ratio.

$$\rho_{SE}\left(\frac{M}{N}\right)=\max_{a\geq 0}\frac{1-\frac{2N}{M}[(1+a^2)\Phi(a)-a\phi(a)]}{1-a^2-2[(1+a^2)\Phi(a)-a\phi(a)]} \tag{23}$$

This paper initializes the average number of active users $\theta^0=0$, this effectively assumes that the active user's $pdf\ f(\cdot)$ is symmetric.

4. EM-BG-AMP algorithm simulation results

This article fully reproduced the EM-BG-AMP algorithm and completed the modeling of the physical background.

The simulation of this article is mainly based on the following physical background: N users are randomly distributed within a circle with a radius of A , and b antennas are centrally distributed at the base station at the center of the circle. At the same time, only K users out of N users are active, that is, the sparsity is K. While N users send a signal with pilot length M to b antennas [9]. The user's channel response is set to large-scale fading plus Rayleigh channel fading, and the noise is set to Additive white Gaussian noise. Use the EM-BG-AMP algorithm for channel estimation and complete active user detection, and evaluate the effectiveness of active user recognition and channel estimation using Normalized Mean squared error (NMSE) and User Error Ratio (UER), respectively.

4.1. The influence of received signal-to-noise ratio on the performance of EM-BG-AMP algorithm

Scenario: In the case of 100 users, 10 active users, 8 antennas, 40 pilot lengths, and a large-scale fading coefficient of 2.5, Figures 1 and 2 respectively depict the performance of the EM-BG-AMP algorithm for channel estimation and active user detection while the received signal-to-noise ratio is changing linearly.

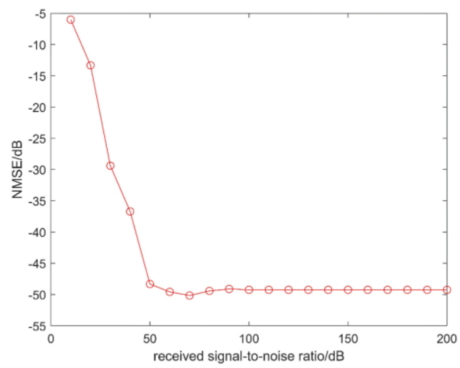

Figure 1. Performance changes of EM-BG-AMP algorithm channel estimation while received signal-to-noise ratios change.

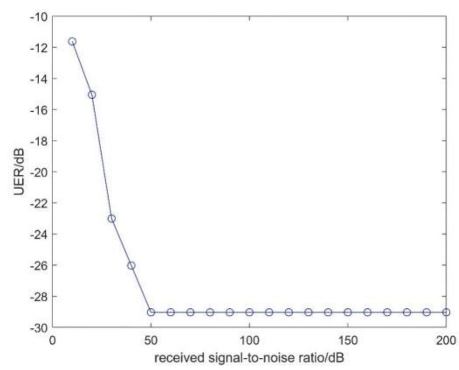

Figure 2. Performance changes in active user detection of EM-BG-AMP algorithm while received signal-to-noise ratios change.

From Figure 1, when the received signal-to-noise ratio is between [0,55] dB, the NMSE of the EM-BG-AMP algorithm decreases as the received signal-to-noise ratio increases. That is to say, within this range, the higher the received signal-to-noise ratio, the better the channel estimation performance of the EM-BG-AMP algorithm, and the smaller the error. The received signal-to-noise ratio continues to increase, and at this time, the channel estimation performance of the EM-BG-AMP algorithm does not significantly improve, with NMSE roughly maintained at -52 dB.

As shown in Figure 2, when the received signal-to-noise ratio increases from 8 dB to 50 dB, UER decreases from -12 dB to -29 dB. When the received signal-to-noise ratio continues to increase from 50 dB, The UER essentially stays the same. That is to say, in this scenario, when the received signal-to-noise ratio is up to 50 dB, the EM-BG-AMP algorithm achieves the best active user detection performance, with an active user detection error rate of -29 dB.

4.2. The effect of sparsity on the EM-BG-AMP algorithm's effectiveness

Sparsity, expressed as the number of active users in the physical background.

Scenario: In the case of 100 users, 30 dB signal-to-noise ratio, 8 antennas, 40 pilot lengths, and a large-scale fading coefficient of 2.5, Figures 3 and 4 respectively depict the performance of the EM-BG-AMP algorithm for channel estimation and active user detection as a function of the sparsity.

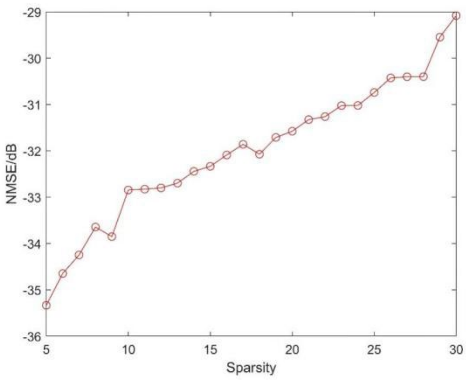

Figure 3. Performance changes of EM-BG-AMP algorithm channel estimation under different sparsity.

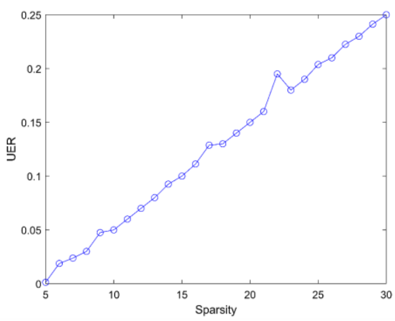

Figure 4. Performance changes in active user detection of EM-BG-AMP algorithm under sparsity.

From Figure 3, as the number of active users increases from 5 to 30, the NMSE of the EM-BG-AMP algorithm continues to increase as the number of active users k increases. Therefore, the more active users in the system, the greater the pressure it brings to the system, and the effectiveness of the EM-BG-AMP algorithm in channel estimation also deteriorates.

From Figures 4, it is evident that there is an almost linear relationship between UER and the number of active users in this system. The number of active users increases from 5 to 30, and UER increases almost linearly from 0 to 0.25. This indicates that as the number of active users increases, the performance of the EM-BG-AMP algorithm for active user detection decreases linearly.

5. Conclusion

This paper concludes that the higher the received signal-to-noise ratio, the better the channel estimation and active user detection effectiveness of EM-BG-AMP. However, after exceeding 60 dB, both performance changes are very small. Therefore, in practical backgrounds, the received signal-to-noise ratio can be set to around 60 dB.

DOI: 10.54254/2755-2721/25/20230779

The higher the sparsity, the worse the channel estimation and active user detection performance of the EM-BG-AMP algorithm. In reality, the sparsity of the Massive Access system is low because of numerous users and only a small part of users sends messages in a certain time [10].

With the in-depth development of 5G and B5G (Beyond 5G), as well as the emergence of sixth generation wireless communication, the rapid development of M2M scenarios and IOTs, large-scale wireless access technology will become increasingly important and have broad application prospects.

The work path of this study suggests that relevant algorithm research in large-scale wireless access situations can be continued to improve the precision of active user recognition and channel estimate. Based on the assumption that the channel model conforms to independently and identically distributed random variables, the iterative termination condition of the EM-BG-AMP algorithm replicated in this paper can take into account how to use compressed sensing theory to estimate the channel and detect active users in correlated channels. Signal processing in non-line of sight channels is more difficult in practical applications since the channel model taken into consideration in this article is a line-of-sight channel.

References

[1] Cotter S F, Rao B D, Engan K, et al. Sparse solutions to linear inverse problems with multiple measurement vectors[J]. IEEE Transactions on Signal Processing, 2005, 53(7):2477-2488.

[2] Ke Malong et al. Compressive Sensing-Based Adaptive Active User Detection and Channel Estimation: Massive Access Meets Massive MIMO[J]. IEEE Transactions on Signal Processing, 2020, 68 : 764-779.

[3] Bayesteh A, Yi E, Nikopour H, et al. Blind detection of SCMA for uplink grant-free multiple-access[C]. In: Wireless Communications Systems (ISWCS), 2014 11th International Symposium on. 2014. 853-857.

[4] Xu X, Rao X, Lau V K. Active user detection and channel estimation in uplink CRAN systems[C]. In: Communications (ICC), 2015 IEEE International Conference on. 2015. 2727-2732.

[5] Candes E J, Romberg J, Tao T. Robust uncertainty principles: exact signal reconstruction from highly incomplete frequency information: IEEE, 10.1109/TIT.2005.862083[P]. 2006.

[6] Candes E J , Tao T . Decoding by linear programming[J]. IEEE Transactions on Information Theory, 2005, 51(12):4203-4215.

[7] Vila J, Schniter P. Expectation-maximization Bernoulli-Gaussian approximate message passing[C]// Signals, Systems & Computers. IEEE, 2011:799-803.

[8] Rangan S. Generalized Approximate Message Passing for Estimation with Random Linea -r Mixing[C]//IEEE International Symposium on Information Theory. IEEE, 2011.DOI: 10.1109/ISIT.2011.6033942.

[9] Schepker H F, Bockelmann C, Dekorsy A. Exploiting sparsity in channel and data estimation for sporadic multi-user communication[C]. In: Wireless Communication Systems (ISWCS 2013), Proceedings of the Tenth International Symposium on. 2013. 1-5.

[10] B. Wang, L. Dai, T. Mir, and J. Li, “Dynamic compressive sensing based multi-user detection for uplink grant-free NOMA,” IEEE Commun. Lett., vol. 20, no. 11, pp. 2320-2323, Nov. 2016.