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Compressive Sensing Based Multi-User Detection for Uplink Grant-Free Non-Orthogonal Multiple Access

Bichai Wang[1], Linglong Dai[1], Yifei Yuan[2], and Zhaocheng Wang[1]

[1]Tsinghua National Laboratory for Information Science and Technology (TNList), Department of Electronic Engineering, Tsinghua University, Beijing 100084, China

[2]ZTE Corporation

wang-bc11@mails.tsinghua.edu.cn

Abstract

In the uplink grant-free non-orthogonal multiple access (NOMA) system, the current near-optimal multi-user detection (MUD) based on message passing algorithm (MPA) assumes that the user activity information is exactly known at the receiver, which is impractical yet challenging. In this poster, inspired by the observation of user sparsity, we jointly use compressive sensing (CS) and MPA to propose a CS-MPA detector to realize both user activity and data detection for uplink grant-free NOMA. Simulation results show that the proposed CS-MPA detector with affordable complexity not only outperforms the conventional MPA detector without user activity information, but also achieves very close performance to the genie-knowledge MPA detector with exact knowledge of user activity, especially when the signal-to-noise ratio (SNR) is high.

Problem Statement

Among available NOMA schemes, low-density spreading (LDS) multiple access is a generic solution, which can be extended to most of other NOMA schemes. In LDS systems, in order to realize interference cancellation among multiple users, MUD based on MPA has been proposed to approximate the optimal maximum a posteriori (MAP) detection. By making full use of the sparsity of LDS structure, the complexity of the MPA-based receiver is relatively low. However, the conventional MPA detector is usually realized based on the assumption that active users are exactly known at the receiver, which is not true in practical systems, especially in the uplink grant-free multiple access systems, where users can randomly transmit data without the complex grant procedure involving high signaling overhead and large delay. Therefore, accurate detection of user activity is required to enable massive connectivity for 5G, while this important issue is rarely investigated in the literature.

In this poster, we jointly use CS and MPA to propose a CS-MPA detector to realize both user activity and data detection in the uplink grant-free LDS systems. This scheme is inspired by the observation that although the number of users/devices is very large in typical scenario of massive connectivity for 5G, the number of simultaneously active users/devices is still limited, i.e., just a small part of all users/devices will transmit data simultaneously. Particularly, according to the statistical data of mobile traffic, even in busy hour, the number of simultaneously active users does not exceed 10% of the total amount of all users. Thus, the sparsity of user activity naturally exists in NOMA, which inspires us to formulate the MUD problem under the CS framework. Then, sparse signal recovery algorithms in CS can be used to reliably detect user activity, and MPA can be performed to realize active users' data detection based on the obtained user activity information. Simulation results demonstrate that the performance of the proposed CS-MPA detector is much better than that of the conventional MPA detector without user activity information, and it can also approach the performance of the genie-knowledge MPA detector assuming the exact knowledge of user activity. Furthermore, we analyze the effect of user sparsity on the performance of the proposed CS-MPA detector, and it is shown that with the increase of the number of active users, the signal detection performance will degrade accordingly, but the proposed CS-MPA detector can still work well even if the user sparsity reaches to 10%, provided that SNR is relatively high.

System Model

We consider a typical uplink NOMA system, i.e., LDS-OFDM, with a base station (BS) and *K* users. As shown in Fig. 1, The bit stream of user *k* is mapped to a constellation point to generate the transmitted symbol x_k. Then, the transmitted symbol is modulated onto a spreading sequence s_k of length *N*. After that, the spreading sequences of all users are superimposed to be transmitted over *N* subcarriers. LDS means the number of nonzero elements in each spreading sequence is much less than *N*. In addition, we consider the case *N* < *K*, i.e., the overloaded system. The received signal on subcarrier *n* can be represented

$$y_n = \sum_{k=1}^{K} g_{nk} s_{nk} x_k + v_n \quad (1)$$

where s_{nk} is the *n*th component of the spreading sequence s_k of user *k*, g_{nk} is the channel gain of user *k* on the *n*th subcarrier, and v_n is a complex-valued noise sample taken from a zero mean Gaussian distribution with variance σ^2.

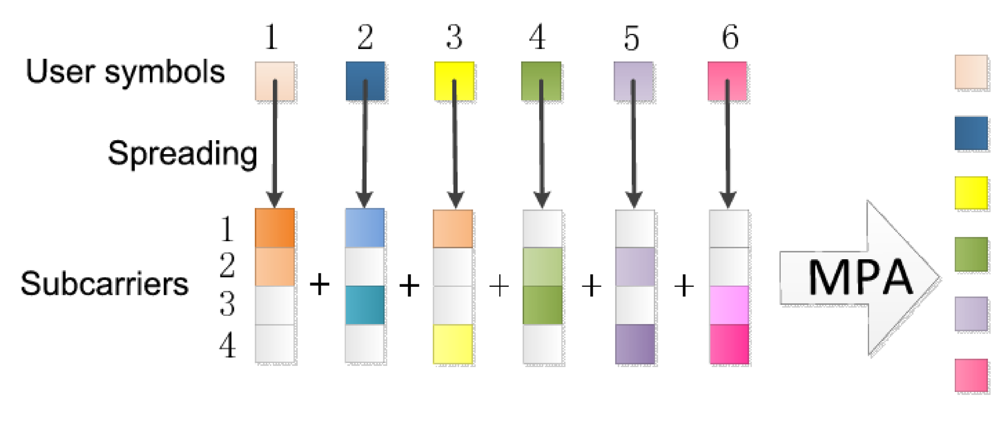

Fig. 1: Graphical representation of LDS-OFDM, where *K* = 6 active users occupied *N* = 4 subcarriers, leading to the overloading factor 150%.

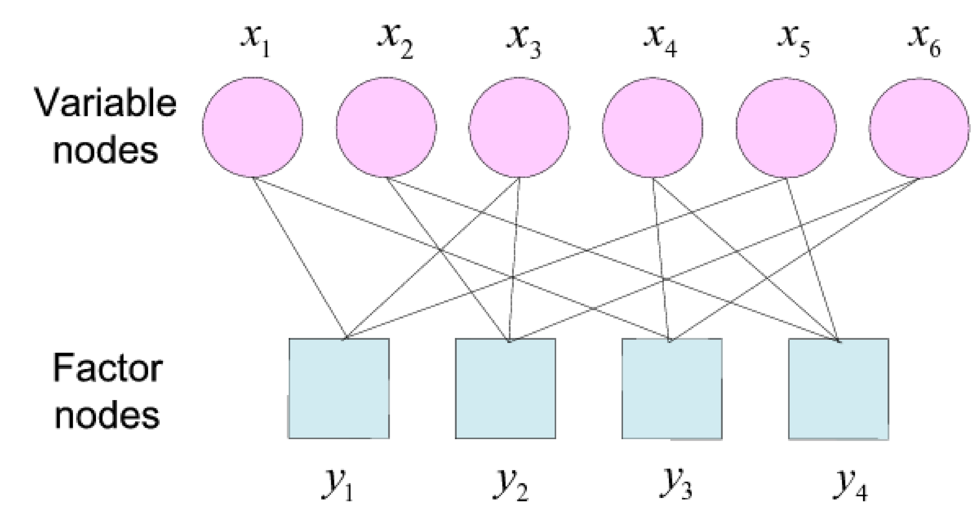

Fig. 2: Factor graph representation of MPA-based receiver including variable nodes and factor nodes.

We combine the received signals from all subcarriers, and then the received signal vector $\mathbf{y} = [y_1, y_2, \cdots, y_N]^T$ over *N* subcarriers at the BS can be expressed as

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{v} \quad (2)$$

Where $\mathbf{x} = [x_1, x_2, \cdots, x_K]^T$, **H** is a matrix of size $N \times K$, whose element h_{nk} in the *n*th row and the *k*th column equals to $g_{nk}s_{nk}$. Finally, $\mathbf{v} = [v_1, v_2, \cdots, v_N]^T$ is the noise vector following the distribution $CN(0, \sigma^2 \mathbf{I}_N)$.

At the receiver, by leveraging the sparsity of LDS structure, MUD based on MPA with acceptable complexity has been proposed to realize data detection. Specifically, MPA can be explained by the factor graph as shown in Fig. 2, in which transmitted symbols for all *K* users are variable nodes, and observations over all *N* subcarriers are factor nodes. In the factor graph, there exists an edge between a variable node x_k and a factor node y_n if and only if $s_{nk} \neq 0$. Message can be passed between connected variable node and factor node through the edge in the factor graph. In MPA, the marginal distribution of a variable node can be regarded as the product of the messages received by that node.

The existing MUD based on MPA assumes that active users are exactly known at the BS receiver. However, in the uplink grant-free LDS-OFDM, users can randomly transmit signals without BS scheduling. As a result, the user activity information cannot be easily obtained, which means user activity detection is the premise of practical MPA-based data detection. In the next section, a CS-MPA detector will be proposed to address this issue.

Proposed CS-MPA Detector

In order to improve the robustness of uplink grant-free NOMA, we propose a CS-MPA detector that can accurately predict the user activity and efficiently perform the data detection for LDS-OFDM. The scheme exploits the user sparsity which is inherent to massive connectivity, and combines CS and MPA as shown in Fig. 3. Specifically, procedures of the proposed CS-MPA detector are described by Algorithm 1 in detail.

We consider the uplink grant-free LDS-OFDM system, where channel gains over *N* subcarriers within the coherent bandwidth remain unchanged but different among different users, i.e., for any $n = 1,2,\cdots,N$, we have $g_{nk} = g_k$, where $k = 1,2,\cdots,K$. Uplink length-*N* reference signals $\mathbf{a}_1, \mathbf{a}_2, \cdots, \mathbf{a}_K$ for *K* users are firstly transmitted, which constitute the observation matrix **A**, i.e., $\mathbf{A} = [\mathbf{a}_1, \mathbf{a}_2, \cdots, \mathbf{a}_K]$. Then, the received signal $\mathbf{y}_1$ for user activity detection can be presented by

$$\mathbf{y}_1 = \sum_{k=1}^{K} \mathbf{a}_k g_k I_k + \mathbf{v}_1 = \mathbf{A}\mathbf{g} + \mathbf{v}_1 \quad (3)$$

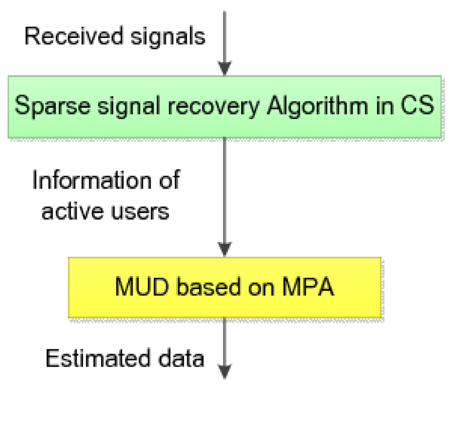

Fig. 3: Diagram representation of the proposed CS-MPA detector.

Where $\mathbf{g} = [g_1 I_1, g_2 I_2, \cdots, g_K I_K]^T$, I_k for $k = 1,2,\cdots,K$ is a logical variable to indicate user *k* is active or not, i.e., $I_k = 1$ if user *k* is active, while $I_k = 0$ if user *k* is inactive, and $\mathbf{v}_1 \sim CN(0, \sigma_1^2 \mathbf{I})$. Thus, **g** is sparse due to the sparsity of user activity inherent in massive connectivity as discussed before. In this way, the estimation of **g** in (3) can be regarded as the problem of sparse signal recovery in CS, only the models with noise need to be considered. Particularly, **A** can be designed to obey the restricted isometry property (RIP) with overwhelming probability. Therefore, sparse signal recovery algorithms in CS can be used to realize user activity detection by identifying the positions of nonzero elements in **g**. Without loss of generality, in this paper, we adopt the compressive sampling matching pursuit (CoSaMP) algorithm due to its low complexity and excellent robustness to noise, so that the user activity can be detected with high accuracy.

Based on the user activity information obtained above, the received signal $\mathbf{y}_2$ of data symbols modulated by sparse spreading sequences can be expressed as

$$\mathbf{y}_2 = \mathbf{H}_2 \mathbf{x}_{\text{active}} + \mathbf{v}_2 \quad (4)$$

where $\mathbf{x}_{active}$ consists of active users' symbols, $\mathbf{H}_2$ has the same form as **H** in (2) except that it only includes channel vectors and spreading sequences for active users, which can be obtained via time or frequency domain training pilots, and $\mathbf{v}_2 \sim CN(0, \sigma_2^2 \mathbf{I})$. Then, MPA can be used to realize data detection.

Input:
1) $\mathbf{y}_1$ and $\mathbf{A}$ in (3), the number of active users s, the maximum iteration number T_1 of CoSaMP;
2) $\mathbf{y}_2$ and $\mathbf{H}_2$ in (4), $\sigma_2{}^2$, the maximum iteration number T_2 of MPA.

Activity detection

CS-based activity detection:
Initialization: $i = 1$, $\mathbf{g}^{(0)} = \mathbf{0}$, $\mathbf{r} = \mathbf{y}_1$, and $\Omega = \emptyset$
while $i \leq T_1$ **do**
  $\mathbf{e} = \mathbf{A}^H \mathbf{r}$; %Form signal proxy
  $\Omega = \text{supp}(\mathbf{e}_{2s})$; %The best $2s$ support
  $T = \Omega \cup \text{supp}(\mathbf{g}^{(i-1)})$; %Merge supports
  $b|_T = \mathbf{A}_T^{\dagger} \mathbf{y}_1$; %Least-squares
  $b|_{T^C} = 0$;
  $\mathbf{g}^{(i)} = b_s$; %New approximation
  $\mathbf{r} = \mathbf{y}_1 - \mathbf{A}\mathbf{g}^{(i)}$; %Residual
  $i = i + 1$.
end while
return $\hat{\mathbf{g}} = \mathbf{g}^{(T_1)}$
location $= find(\hat{\mathbf{g}} \neq 0)$ and $\mathbf{x}_{\text{active}} = \mathbf{x}(\text{location})$

Data detection

MPA-based data detection:
Initialization: $i = 1$, $m_{n\to k}^{(0)}(x_k) = 1$ and $m_{k\to n}^{(0)}(x_k) = 0, \forall\, k, n$
while $i \leq T_2$ **do**
  $m_{n\to k}^{(t)}(x_k) \propto \sum_{\{x_i | i\in N(n)\backslash k\}} \frac{1}{\sqrt{2\pi}\sigma_2} \exp\{-\frac{1}{2\sigma_2{}^2}\|y_{2,n} - h_{2,nk}x_k - \sum_{i\in N(n)\backslash k} h_{2,ni}x_i\|^2\} \cdot \prod_{i\in N(n)\backslash k} m_{i\to n}^{(t-1)}(x_i)$
  $m_{k\to n}^{(t)}(x_k) \propto \prod_{i\in N(k)\backslash n} m_{i\to k}^{(t-1)}(x_k)$
end while
return $p(x_k) \propto \prod_{n\in N(k)} m_{n\to k}^{(T_2)}(x_k)$

Output:
Estimated active users' data $\hat{\mathbf{x}}_{\text{active}}$

Algorithm 1: Proposed CS-MPA detector

Simulation Results

We analyze the bit error rate (BER) performance of the proposed CS-MPA detector in Rayleigh fading channel with QPSK modulation. The length of reference signals is *N* = 40, and the number of users is *K* = 80. Therefore, the overloading factor is 200%. Nonzero values for each row of the spreading matrix whose column vectors consist of spreading sequences are taken from a constellation set.

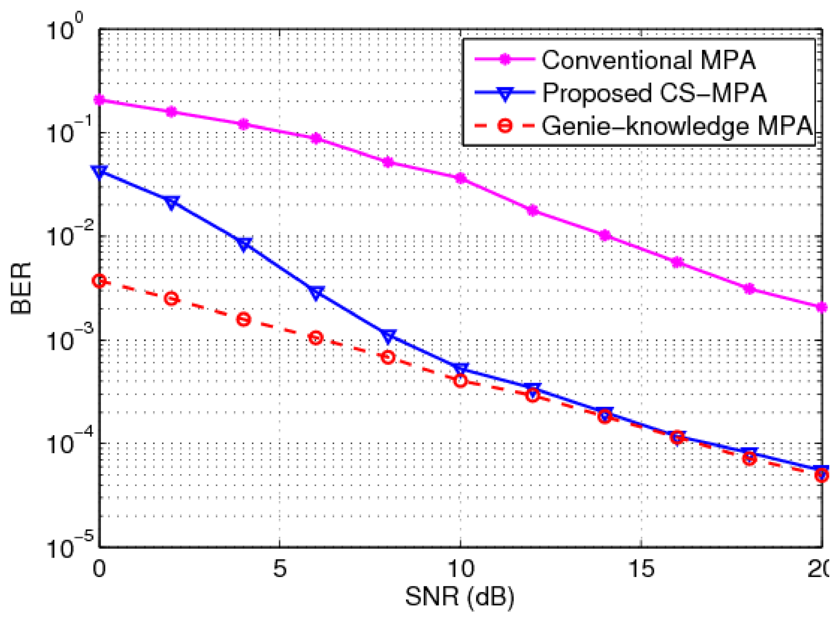

Fig. 4: BER performance of the proposed CS-MPA detector

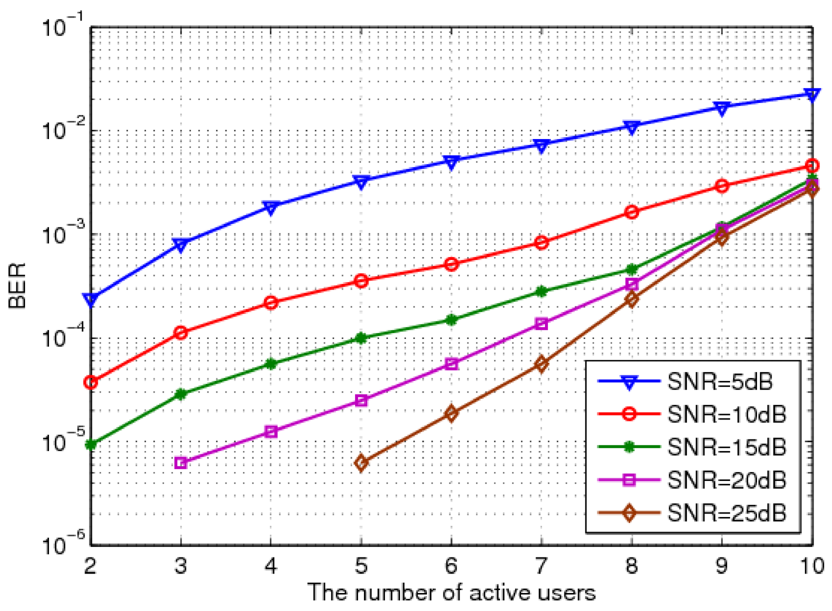

Fig. 5: The effect of the number of active users on the BER performance of the proposed CS-MPA detector

Fig. 4 compares the BER performance of the following three detectors: the proposed CS-MPA, conventional MPA without user activity information, and the genie-knowledge MPA assuming the exact knowledge of user activity. In the conventional MUD based on MPA without user activity information, we apply MPA to all users with extended constellation, i.e., the constellation is expanded to 4 points plus zero point, while the performance of the genie-knowledge MPA can provide the lower bound for comparison. Particularly, we assume that there are s = 6 active users in this simulation. From Fig. 4, we can find that the proposed CS-MPA detector significantly outperforms the conventional MPA detector due to the user activity can be reliably detected. Meanwhile, the performance of the CS-MPA detector is very close to that of the genie-knowledge MPA detector when SNR is relatively high, e.g., SNR > 15 dB.

Fig. 5 illustrates the effect of the number of active users on the BER performance of the proposed CS-MPA detector. We can find that with the increase of the number of active users, the signal detection performance will be degraded. In addition, it is also shown that when the SNR is relatively high, the proposed CS-MPA detector can still work well even if the number of active users becomes large, e.g., when SNR > 15 dB, the BER will not exceed 10^{-3} even though the number of active users reaches 9, i.e., the user sparsity level is over 10%. Note that we have mentioned in the section of Problem Statement that even in busy hour, the number of active users does not exceed 10% of the amount of all users according to the statistical data. Therefore, the proposed CS-MPA detector can be used in practical scenarios of massive connectivity for 5G with high detection reliability.

Conclusions

In this paper, we have proposed a CS-MPA detector to jointly realize user activity detection and data detection with acceptable complexity in the uplink grant-free NOMA for 5G. It is shown that the conventional MPA receiver without user activity information cannot work well, while the proposed CS-MPA receiver enjoys the BER performance very close to the genie-knowledge MPA detector with exact user activity information, especially with high SNR. In this way, uplink grant-free transmission becomes feasible in NOMA, which can significantly reduce latency and signaling overhead for 5G with massive connectivity. Note that the proposed CS-MPA detector can be also generalized to most of other NOMA schemes such as SCMA, MUSA, and SAMA.