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
E-mail: wang-bc11@mails.tsinghua.edu.cn

***Abstract*—Non-orthogonal multiple access (NOMA) has become one of the promising key technologies for future 5G wireless communications to improve spectral efficiency and support massive connectivity. However, in the uplink grant-free 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 due to anyone of massive users can randomly enter or leave the system. In this paper, 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. Specifically, the MUD problem is firstly formulated under CS framework by exploiting user sparsity, and then user activity can be detected by sparse signal recovery algorithms in CS. Then, MPA can be performed to reliably detect active users' data. It is shown 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.**

I. Introduction

In the history of wireless communications, multiple access has become one of the key revolutionary technologies to distinguish different mobile communication systems. Specifically, from the 1G to the current 4G wireless communications, frequency division multiple access (FDMA), time division multiple access (TDMA), code division multiple access (CDMA), and orthogonal frequency division multiple access (OFDMA) have been extensively investigated, respectively, which belong to the category of orthogonal multiple access (OMA) in terms of their design principles. However, in these conventional OMA schemes, the maximum number of supportable users is restricted by the amount of available orthogonal resources, which makes OMA difficult to meet the explosive demand of massive connectivity for 5G [1] [2]. To this end, some non-orthogonal multiple access (NOMA) technologies have been recently investigated to realize massive connectivity by introducing controllable interference at the cost of slightly increased receiver complexity. Current NOMA solutions can be basically divided into two categories, i.e., power domain multiplexing such as basic power-domain NOMA [3]–[6], and code domain multiplexing which includes low-density spreading (LDS) multiple access [7]–[10], sparse code multiple access (SCMA) [11]–[14], multi-user shared access (MUSA), successive interference cancelation amenable multiple access (SAMA) [15], etc. Among these available NOMA schemes, LDS-OFDM is a generic solution, which can be extended to most of other NOMA schemes.

In LDS-OFDM systems, in order to realize interference cancellation among multiple users, multi-user detection (MUD) based on message passing algorithm (MPA) has been proposed to approximate the optimal maximum a *posteriori* (MAP) detection [7]–[12], [15]. By making full use of the sparsity of LDS structure in LDS-OFDM, 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 paper, we jointly use compressive sensing (CS) and MPA to propose a CS-MPA detector to realize both user activity and data detection in the uplink grant-free LDS-OFDM 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 [16] [17], 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 [18]. Then, sparse signal

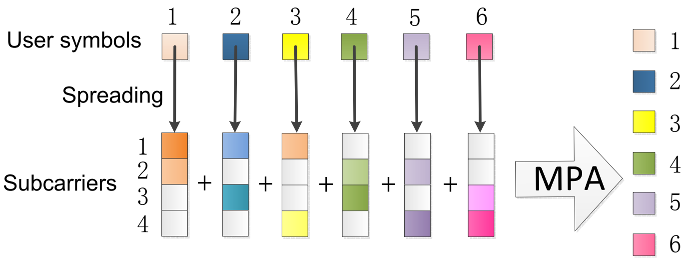

Fig. 1. Graphical representation of LDS-OFDM, where $K = 6$ active users occupied $N = 4$ subcarriers, leading to the overloading factor 150%.

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.

The rest of this paper is organized as follows. The system model of LDS-OFDM will be discussed in Section II, and in Section III, we will explain the proposed CS-MPA detector in detail. Then, in Section IV, we will analyze the performance of the CS-MPA detector in terms of bit error rate (BER). Finally, conclusions are drawn in Section V.

II. 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, i.e., x_k is taken from a complex-constellation set $\mathbb{X}$. Then, the transmitted symbol is modulated onto a spreading sequence $\mathbf{s}_k$ 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 overloading to enable massive connectivity can be realized, which is the key feature of NOMA. The received signal on subcarrier n can be represented by

$$y_n = \sum_{k=1}^{K} g_{n,k} s_{n,k} x_k + v_n, \tag{1}$$

where $s_{n,k}$ is the nth component of the spreading sequence $\mathbf{s}_k$ of user k, $g_{n,k}$ is the channel gain of user k on the nth subcarrier, and v_n is a complex-valued noise sample taken from a zero mean Gaussian distribution with variance σ^2.

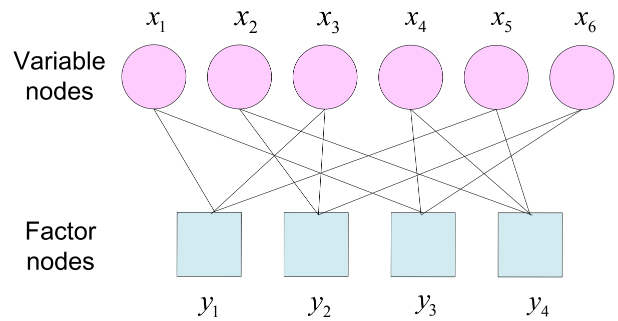

Fig. 2. Factor graph representation of MPA-based receiver including variable nodes and factor nodes.

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

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{v}, \tag{2}$$

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

We can see from (1) that when all $\mathbf{s}_k$ for $k = 1, 2, \cdots, K$ are sparse spreading sequences, each user will spread its data only over a small number of subcarriers. As a result, the number of the superimposed signals on each subcarrier will be less than the number of active users, which means the interference can be efficiently decreased among users with appropriate design of spreading sequences. Then, (1) can be also rewritten as

$$y_n = \sum_{k \in N(n)} g_{n,k} s_{n,k} x_k + v_n = \sum_{k \in N(n)} h_{n,k} x_k + v_n, \tag{3}$$

where $N(n)$ expresses the set of users whose sparse spreading sequence has a nonzero element on subcarrier n, namely $N(n) = \{k | s_{n,k} \neq 0\}$.

In LDS-OFDM, a key point is how to design the sparse spreading sequence for each user, which has a big impact on the effect of interference cancellation at the receiver. The basic requirement is that the unique decodability must be guaranteed, which means that there should not exist two different input vectors combined by symbols from all users that yield the same received vector. In addition, the position selection of nonzero elements is another important design issue. Particularly, the overlaps of users' spreading sequences on each subcarrier should be minimized. Therefore, if the larger diversity of nonzero elements' positions of different users is carried out, the better performance will be achieved. After positions of nonzero elements have been determined, we should then consider how to choose the nonzero values for each spreading sequence. Intuitively, nonzero values superimposed on the same subcarrier should be distinct. One promising method is to take different values from a complex-valued constellation for these nonzero elements [7].

At the receiver of LDS-OFDM, 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 [19] as shown in Fig. 2, in which transmitted symbols for all K users are variable nodes $\{x_k\}_{k=1}^{K}$, and observations over all N subcarriers are factor nodes $\{y_n\}_{n=1}^{N}$. In the factor graph, there exists an edge between a variable node x_k and a factor node y_n if and only if $s_{n,k} \neq 0$. 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. More specifically, the iterative form of MPA in the tth iteration can be represented by

$$\begin{aligned} m_{n\to k}^{(t)}\left(x_k\right) \propto & \sum_{\{x_i|i\in N(n)\backslash k\}} \frac{1}{\sqrt{2\pi}\sigma} \exp\{-\frac{1}{2\sigma^2}||y_n - h_{n,k}x_k \\ & - \sum_{i\in N(n)\backslash k} h_{n,i}x_i||^2\} \prod_{i\in N(n)\backslash k} m_{i\to n}^{(t-1)}\left(x_i\right), \end{aligned} \tag{4}$$

$$m_{k\to n}^{(t)}\left(x_k\right) \propto \prod_{i\in N(k)\backslash n} m_{i\to k}^{(t-1)}\left(x_k\right), \tag{5}$$

where $m_{n\to k}^{(t)}\left(x_k\right)$ denotes the message passed from factor node y_n to variable node x_k in the tth iteration, $m_{k\to n}^{(t)}\left(x_k\right)$ presents the message passed from variable node x_k to factor node y_n, and $N(n)\backslash k$ presents all elements in $N(n)$ except for k. After T times of iterations, the (approximate) marginal probability distribution of x_k can be calculated by

$$p\left(x_k\right) \propto \prod_{i\in N(k)} m_{i\to k}^{(T)}\left(x_k\right). \tag{6}$$

Finally, each estimated symbol of active users is taken from $\mathbb{X}$ with the maximum marginal probability.

Compared with the optimal MUD based on MAP, the complexity of the MPA receiver is exponential to the maximum number of symbols spreading over the same subcarrier w rather than the number of totally transmitted symbols K, where $w < K$ due to LDS structure. 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.

III. 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.

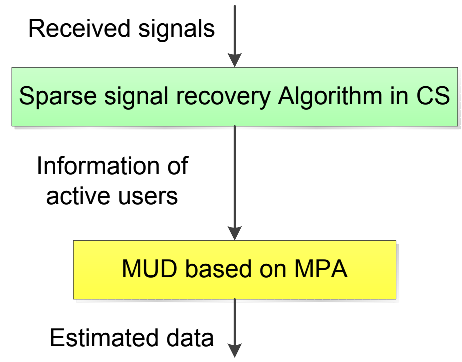

Fig. 3. Diagram representation of the proposed CS-MPA detector.

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 $g_{n,k} = g_k$, 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 $\mathbf{A}$, i.e., $\mathbf{A} = [\mathbf{a}_1, \mathbf{a}_2, \cdots, \mathbf{a}_K]_{N\times K}$. Then, the received signal $\mathbf{y}_1$ for user activity detection can be presented by

$$\mathbf{y}_1 = \sum_{k=1}^{K} \mathbf{a}_k g_k I_k + \mathbf{v}_1 = \mathbf{A}\mathbf{g} + \mathbf{v}_1, \tag{7}$$

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 $\mathbf{v}_1 \sim \mathcal{CN}\left(0, {\sigma_1}^2\mathbf{I}\right)$. Thus, $\mathbf{g}$ is sparse due to the sparsity of user activity inherent in massive connectivity as discussed before. In this way, the estimation of $\mathbf{g}$ in (7) can be regarded as the problem of sparse signal recovery in CS, only the models with noise need to be considered. Particularly, $\mathbf{A}$ can be designed to obey the restricted isometry property (RIP) with overwhelming probability [18]. Therefore, sparse signal recovery algorithms in CS can be used to realize user activity detection by identifying the positions of nonzero elements in $\mathbf{g}$. Without loss of generality, in this paper, we adopt the compressive sampling matching pursuit (CoSaMP) algorithm [20] due to its low complexity and excellent robustness to noise, so that the user activity can be detected with high accuracy. In CoSaMP, the strongest s components of the original sparse signal are identified in an iterative manner, and during each iteration, CoSaMP performs five major steps as follows [20]:

- Identification: This algorithm forms a signal proxy of the residual and identifies large components of the proxy by calculating the best $2s$ support.
- Merger supports: The set of newly identified components obtained in the previous step is combined with the set of components in the current approximation.
- Estimation: A least-squares problem is solved to approximate the target signal on the merged set of components.

Input:

1) $\mathbf{y}_1$ and $\mathbf{A}$ in (7), the number of active users s, the maximum iteration number T_1 of CoSaMP;

2) $\mathbf{y}_2$ and $\mathbf{H}_2$ in (8), ${\sigma_2}^2$, the maximum iteration number T_2 of MPA.

CS-based activity detection:

Initialization: $i = 1$, $\mathbf{g}^{(0)} = \mathbf{0}$, $\mathbf{r} = \mathbf{y}_1$, and $\Omega = \emptyset$

while $i \le T_1$ **do**

  $\mathbf{e} = \mathbf{A}^{\mathrm{H}}\mathbf{r}$; %Form signal proxy

  $\Omega = \mathrm{supp}(\mathbf{e}_{2s})$; %The best $2s$ support

  $T = \Omega \cup \mathrm{supp}(\mathbf{g}^{(i-1)})$; %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 $\mathbf{x}_{\text{active}} = \mathbf{x}(\text{location})$

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 $i \le T_2$ **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

- New approximation: The new approximation is produced by retaining only the largest entries in the estimated least-squares signal.
- Residual: The residual is calculated to update the samples, which can be used for the next iteration.

CoSaMP algorithm can accurately detect positions of nonzero elements of sparse signals by exploiting the inherent sparsity of signals, so that the random user activity can be detected with high accuracy, especially when the signal-to-noise ratio (SNR) is high. Note that in the proposed CS-MPA detector, we are only interested in the support detection of the sparse signal $\mathbf{g}$ to identify the active users, while classical CS algorithms try to detect both the support and specific values of nonzero elements of the sparse signal.

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

$$\mathbf{y}_2 = \mathbf{H}_2\mathbf{x}_{\text{active}} + \mathbf{v}_2, \tag{8}$$

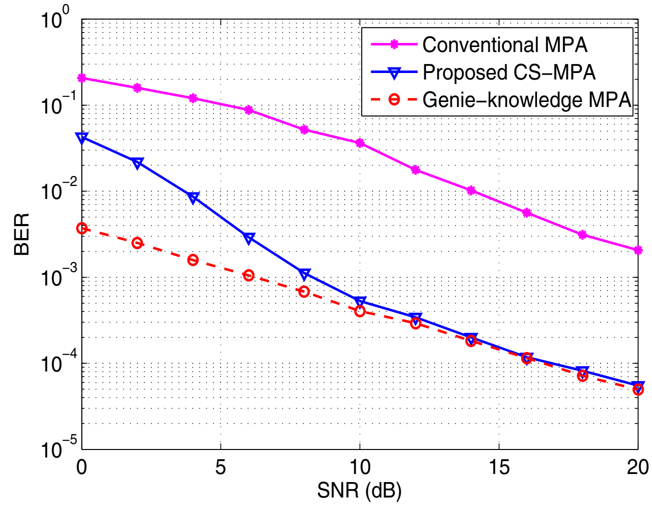

Fig. 4. BER performance of the proposed CS-MPA detector.

where $\mathbf{x}_{\text{active}}$ consists of active users' symbols, $\mathbf{H}_2$ has the same form as $\mathbf{H}$ 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 [21], and $\mathbf{v}_2 \sim \mathcal{CN}\left(0, {\sigma_2}^2\mathbf{I}\right)$. Then, MPA can be used to realize data detection as discussed in Section II.

The proposed CS-MPA detector combines the advantages of CS and MPA to simultaneously realize user activity and data detection. CoSaMP algorithm can accurately detect the support of sparse signals, especially with high SNR, and the computational complexity of the CoSaMP algorithm is upper bounded by $\mathcal{O}(sNK)$. Meanwhile, MPA can approximate the optimal MUD very well with appropriate LDS structure, while the complexity is $\mathcal{O}(|\mathbb{X}|^w)$, where $|\mathbb{X}|$ denotes the cardinality of $\mathbb{X}$. Therefore, CS-MPA can be used in the uplink grant-free LDS-OFDM with high reliability and acceptable complexity.

IV. 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, which is similar to the spreading sequence design in [7].

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

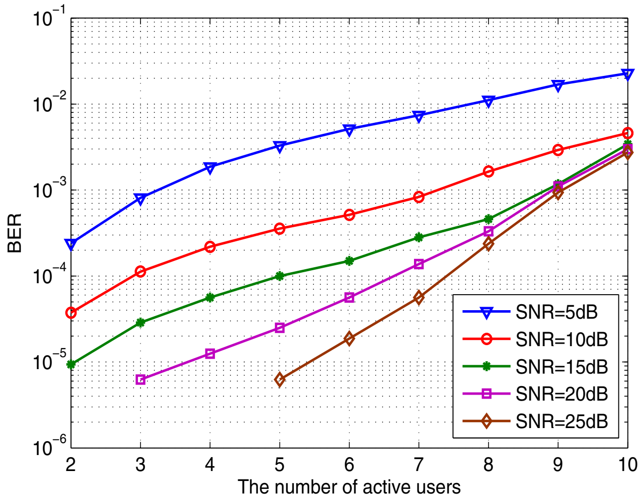

Fig. 5. BER performance of the proposed CS-MPA detector.

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 Section II 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 [16] [17]. Therefore, the proposed CS-MPA detector can be used in practical scenarios of massive connectivity for 5G with high detection reliability.

V. 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.

Acknowledgement

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References

[1] F. Boccardi, R. W. Heath Jr, A. Lozano, T. L. Marzetta, and P. Popovski, "Five disruptive technology directions for 5G," *IEEE Commun. Mag.*, vol. 52, no. 2, pp. 74–80, Feb. 2014.

[2] A. Osseiran, F. Boccardi, V. Braun, K. Kusume, P. Marsch, M. Maternia, O. Queseth, M. Schellmann, H. Schotten, H. Taoka, *et al.*, "Scenarios for 5G mobile and wireless communications: The vision of the METIS project," *IEEE Commun. Mag.*, vol. 52, no. 5, pp. 26–35, May 2014.

[3] Y. Saito, Y. Kishiyama, A. Benjebbour, T. Nakamura, A. Li, and K. Higuchi, "Non-orthogonal multiple access (NOMA) for future radio access," in *Proc. IEEE VTC Spring 2013*, June 2013, pp. 1–5.

[4] A. Benjebbour, Y. Saito, Y. Kishiyama, A. Li, A. Harada, and T. Nakamura, "Concept and practical considerations of non-orthogonal multiple access (NOMA) for future radio access," in *Proc. ISPACS 2013*, Nov. 2013, pp. 770–774.

[5] N. Nonaka, Y. Kishiyama, and K. Higuchi, "Non-orthogonal multiple access using intra-beam superposition coding and SIC in base station cooperative MIMO cellular downlink," in *Proc. IEEE VTC Fall 2014*, Sep. 2014, pp. 1–5.

[6] A. Benjebbovu, A. Li, Y. Saito, Y. Kishiyama, A. Harada, and T. Nakamura, "System-level performance of downlink NOMA for future LTE enhancements," in *IEEE GLOBECOM 2013*, Dec. 2013, pp. 66–70.

[7] J. Van De Beek and B. M. Popovic, "Multiple access with low-density signatures," in *Proc. IEEE GLOBECOM 2009*, Dec. 2009, pp. 1–6.

[8] M. Al-Imari, M. A. Imran, and R. Tafazolli, "Low density spreading for next generation multicarrier cellular systems," in *Proc. IEEE ICFCN 2012*, Apr. 2012, pp. 52–57.

[9] M. Al-Imari, P. Xiao, M. A. Imran, and R. Tafazolli, "Uplink non-orthogonal multiple access for 5G wireless networks," in *Proc. 11th International Symposium on Wireless Communications Systems (ISWCS)*, Aug. 2014, pp. 781–785.

[10] R. Razavi, M. Al-Imari, M. A. Imran, R. Hoshyar, and D. Chen, "On receiver design for uplink low density signature OFDM (LDS-OFDM)," *IEEE Trans. Commun.*, vol. 60, no. 11, pp. 3499–3508, Nov. 2012.

[11] H. Nikopour and H. Baligh, "Sparse code multiple access," in *Proc. IEEE PIMRC 2013*, Sep. 2013, pp. 332–336.

[12] K. Au, L. Zhang, H. Nikopour, E. Yi, A. Bayesteh, U. Vilaipornsawai, J. Ma, and P. Zhu, "Uplink contention based SCMA for 5G radio access," in *Proc. IEEE GLOBECOM 2014*, Dec. 2014, pp. 1–5.

[13] M. Taherzadeh, H. Nikopour, A. Bayesteh, and H. Baligh, "SCMA codebook design," in *Proc. IEEE VTC Fall 2014*, Sep. 2014, pp. 1–5.

[14] H. Nikopour, E. Yi, A. Bayesteh, K. Au, M. Hawryluck, H. Baligh, and J. Ma, "SCMA for downlink multiple access of 5G wireless networks," in *Proc. IEEE GLOBECOM 2014*, Dec. 2014, pp. 1–5.

[15] X. Dai, S. Chen, S. Sun, S. Kang, Y. Wang, Z. Shen, and J. Xu, "Successive interference cancelation amenable multiple access (SAMA) for future wireless communications," in *Proc. IEEE ICCS 2014*, Nov. 2014, pp. 1–5.

[16] G. Szabo, D. Orincsay, B. P. Gero, S. Gyori, and T. Borsos, "Traffic analysis of mobile broadband networks," in *Proc. WICON*, June 2007, pp. 1–8.

[17] J.-P. Hong, W. Choi, and B. D. Rao, "Sparsity controlled random multiple access with compressed sensing," *IEEE Trans. Wireless. Commun.*, vol. 14, no. 2, pp. 998–1010, Feb. 2015.

[18] Z. Han, H. Li, and W. Yin, *Compressive sensing for wireless networks*. Cambridge University Press, Jul. 2013.

[19] F. R. Kschischang, B. J. Frey, and H.-A. Loeliger, "Factor graphs and the sum-product algorithm," *Trans. Inf. Theory*, vol. 47, no. 2, pp. 498–519, Feb. 2001.

[20] D. Needell and J. A. Tropp, "CoSaMP: Iterative signal recovery from incomplete and inaccurate samples," *Appl. Comput. Harmonic Anal.*, vol. 26, no. 3, pp. 301–321, May 2009.

[21] L. Dai, Z. Wang, and Z. Yang, "Spectrally efficient time-frequency training OFDM for mobile large-scale MIMO systems," *IEEE J. Sel. Areas Commun.*, vol. 31, no. 2, pp. 251–263, Feb. 2013.