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RESEARCH

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Compressed spectrum sensing for grant-free NOMA based internet of vehicles

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Abstract

With the development of communication technology, non-orthogonal multiple access (NOMA) technology is proposed to meet the requirements of high throughput and low latency in massive machine type communication (mMTC) of Internet of Vehicles (IoV). In grant-free NOMA based IoV, mMTC has the characteristics of sparse active users at the same time, which makes the detection and recovery of user information critical. In this paper, considering the sparsity of active users in mMTC, we present a new block sparsity method under compressed sensing model that enables us to detect activity of users and recover user information with high accuracy and low complexity. The recovered algorithm used in our study is known as block sparse ISD algorithm, which exploits block sparse structure based on the ISD algorithm. The simulation results show that the proposed method is able to realize more performance gains in sparse signal recovery than traditional algorithm.

Keywords: IoV, MMTC, Non-orthogonal multiple access (NOMA), Compressed sensing, Block-sparsity

1 Introduction

In recent years, Internet of Vehicles (IoV) has developed rapidly. The emergence of 5G IoV has greatly improved the communication performance of IoV by using new multiple access technology. 4G mobile communications adopt orthogonal multiple access (OMA) technology to allocate a single wireless resource block to a user. The traditional OMA can not meet the requirements of high-rate and low-latency communications in massive machine type communication (mMTC) of 5G. Non-orthogonal multiple access (NOMA) has been proposed as an ideal uplink communication scheme in the mMTC. Especially in IoV, NOMA is a very promising technology. Unlike traditional OMA method used in the IoV, one resource block can only be allocated to one user. In the NOMA for IoV, by actively introducing interference and then demodulating at the receiver, the same resource block will be allocated to multiple users to improve spectrum efficiency Therefore, the NOMA will meet the demands of high throughput and massive connectivity in 5G IoV.

Grant-base spectrum access is not suitable for mMTC due to the frequent handshake and complex scheduling request. However, without scheduling request and scheduling grant, the grant-free NOMA greatly reduces signaling overhead and latency, which is appropriate for the uplink transmissions of mMTC [1]. Grant-free can also be applied to satellite IoV to make vehicle navigation more efficient. Each active vehicle directly transmits its metadata and data to the satellite without waiting for any permission. The grant-free NOMA allows massive users to access the spectrum, but only a few of them are active at the same time. Therefore, due to the sparse activity among all users, the transmitted symbols of all users form a sparse signal vector [2]. And it is significant to detect the active users and recover the sparse signals in the decoding of the grant-free NOMA. Each user is assigned a unique pilot sequence in the grant-free NOMA, and the base station first detects the active users according to the pilot sequences and then recovers the sparse signals with the reconstruction algorithm [3]. According to the sparsity of active users, the reconstruction problem of the sparse signals can be solved by the reconstruction algorithm of compressed sensing (CS), such as Orthogonal Matching Pursuit (OMP) and Iterative Support Detection (ISD) [4]. Different from the traditional OMP algorithm [5], the support set of the ISD algorithm will be completely updated after each iteration, which can correct the support set obtained in the previous iteration in order to improve the accuracy of recovery. SISD algorithm is proposed to jointly recover multiple sparse signals instead of a single sparse signal in several continual time slots by exploiting the structured sparsity [6]. Above these algorithms mainly focus on sparse signals without additional structure, where non-zero elements can appear anywhere in sparse signal vector. In practice, sparse signal vector usually has a strcture, where non-zero elements are distributed according to a certain principal [7, 8].

In this letter, we propose a multiuser detection scheme for iterative support detection algorithm based block sparsity by expoiting the correlation of user activity, which can divide a complete signal vector into several block vectors to reduce the sparsity of a single vector. According to the principle of compressed sensing, the sparser the signal is, the higher the signal recovery accuracy is. Hence, due to the sparsity of each block vector is lower than that of the complete signal vector, the recovery accuracy of the block vector is improved, which can enhance the recovery performance of the complete signal vector. Specifically, all zero elements and non-zero elements in the sparse signal vector are equally allocated to several block vectors, where the indexes of non-zero elements are the same. In this way, block sparsity in the sparse signal recovery model is generated. The main contributions of this letter can be summarized as follows: (1) a iterative support detection algorithm based block sparsity is proposed, where block vectors share a common support within a frame in the grant-free NOMA network. And the support set in each block vector is updated jointly during the iteration in the model. Compared with the random sparsity of active users appearing randomly in sparse signal vector in traditional model, the block sparsity structure can obtain better signal recovery performance by reducing the signal vector sparsity. The proposed ISD algoithm based block sparsity has more performance gain in recovery accuracy than the classic algorithm such as OMP algorithm and ISD algorithm. (2) A circulant matrix is designed as measurement matrix by observing the block structure. The proposed circulant matrix consisting of multiple one-dimensional vectors can further reduces the computation complexity, which is obtained by circularly shifting all the elements in a one-dimensional vector by one bit [9, 10].

2 System model

We consider the uplink transmission in NOMA network consisting of M users and a base station. Without loss of generality, We assume that the BS and all users are equipped with a single antenna. Since there are few users transmitting data at the same time, the number of active users can be set to N, $N \ll M$. According to the sparsity of active users, the original sparse signal b_m is encoded by LDPC and modulated by QPSK to generate symbols B_m. Then the symbol B_m is extended onto a spreading sequence s_m of length K, $K < M$. In the NOMA network, the number of orthogonal subcarriers is K, and each orthogonal subcarrier carries M user signals. Therefore, the signal on the ath subcarrier received by the base station can be expressed as [11, 12]:

$$y_a = \sum_{m=1}^{M} g_{am} s_{am} x_m + v_a \tag{1}$$

where g_{am} is the channel gain of the mth user on the ath subcarrier, s_{am} is the ath component of spreading sequence s_m. v_a is additive white Gaussian noise on the ath subcarrier.

In this letter, we divide the signal into d blocks equally, and the number of users and the number of active users in each block are M/d and K/d respectively. The active users appear at the beginning of each block. Then data of each block transmitted through the subcarrier arrive at the base station. The signal on the ath subcarrier of the ith block received by the base station can be expressed as:

$$y_a^{[i]} = \sum_{m=1}^{M/d} g_{am}^{[i]} s_{am}^{[i]} x_m^{[i]} + v_a^{[i]} \tag{2}$$

where $i \in \{1, 2, \ldots, d\}$, $a \in \{1, 2, \ldots, K/d\}$, $g_{am}^{[i]}$ is the channel gain of the mth user on the ath subcarrier of the ith block, $s_{am}^{[i]}$ is the ath component of spreading sequence s_m of the ith block, $v_a^{[i]}$ is the additive Gaussian white noise with zero mean on the ath subcarrier of the ith block. Small-scale fading channel such as Rayleigh channel can be selected as the channel model. At last we can express the relationship between original sparse signal x and signal block $x^{[i]}$ in the form of one-dimensional matrix

$$x = [x^{[1]}, x^{[2]}, x^{[3]}, \ldots, x^{[d]}]^T \tag{3}$$

where signal block $x^{[i]}$ can be represented as

$$x^{[i]} = [x_1^{[i]}, x_2^{[i]}, x_3^{[i]}, \ldots, x_{M/d}^{[i]}]^T \tag{4}$$

The relationship between the signal block $y^{[i]}$ and the complete signal y received at the base station is

$$y = [y^{[1]}, y^{[2]}, y^{[3]}, \ldots, y^{[d]}]^T \tag{5}$$

where signal block $y^{[i]}$ recevied at the base station can be represented as

$$y^{[i]} = [y_1^{[i]}, y_2^{[i]}, y_3^{[i]}, \ldots, y_{K/d}^{[i]}]^T \tag{6}$$

According to (2), $y^{[i]}$ can be expressed in matrix form as

$$y^{[i]} = A^{[i]}x^{[i]} + v^{[i]} \tag{7}$$

According to (5) and (7), the complete signal y can be represented as

$$\begin{aligned} y &= [y^{[1]}, y^{[2]}, y^{[3]}, \ldots, y^{[d]}]^T \\ &= [A^{[1]}x^{[1]}, A^{[2]}x^{[2]}, A^{[3]}x^{[3]}, \ldots, A^{[d]}x^{[d]}]^T \\ &\quad + [v^{[1]}, v^{[2]}, v^{[3]}, \ldots, v^{[d]}]^T \end{aligned} \tag{8}$$

where $A^{[i]}$ is the channel matrix of the ith block, the size is $K/d \times M/d$. Combining (2) and (7), we can get the expression of the $A^{[i]}$ and channel noise matrix of the ith block $v^{[i]}$

$$A^{[i]} = \begin{bmatrix} A_1^{[i]} \\ A_2^{[i]} \\ A_3^{[i]} \\ \cdots \\ A_{\frac{K}{d}}^{[i]} \end{bmatrix} = \begin{bmatrix} g_{11}^{[i]} & g_{12}^{[i]} & \cdots & g_{1\frac{M}{d}}^{[i]} \\ g_{21}^{[i]} & g_{22}^{[i]} & \cdots & g_{2\frac{M}{d}}^{[i]} \\ g_{31}^{[i]} & g_{32}^{[i]} & \cdots & g_{3\frac{M}{d}}^{[i]} \\ \cdots & \cdots & \cdots & \cdots \\ g_{\frac{K}{d}1}^{[i]} & g_{\frac{K}{d}2}^{[i]} & \cdots & g_{\frac{K}{d}\frac{M}{d}}^{[i]} \end{bmatrix} \tag{9}$$

$$v^{[i]} = [v_1^{[i]}, v_2^{[i]}, v_3^{[i]}, \ldots, v_{\frac{K}{d}}^{[i]}] \tag{10}$$

where elements of the $v^{[i]}$ follow zero mean Gaussian distribution.

3 The block sparse ISD methord

Massive machine type communication (mMTC) is a significant scenario in 5g Internet of Things, whose main characteristics are massive connection, sporadic transmissions and so on. Sporadic transmissions mean the probability of each user being active is very low so that only a small percentage of users are active in communicating with the base station at the same time. So we can propose the sparsity of active users by taking advantage of this characteristic, which forms a sparse signal recovery problem [13]. Compressed sensing can be used to solve this problem effectively. In this letter, signals from inactive users are set to zero and the signals from active users are selected from constellation set $Y, Y = \{1+i, 1-i, -1+i, -1-i\}$. In the traditional CS model, the sparsity of users signals x is often considered, and active users can appear anywhere in x. In this letter, we propose a block sparse method that divides users into blocks and represent x as a combination of signal block $x^{[i]}$. Furthermore, active users appearing at the beginning of each block share the common support, making the best use of block sparsity. Then each block is recovered by reconstruction algorithm. In this way, the degree of freedom of the solution can be reduced and the robustness of the system can be improved, which can bring better recovery performance than traditional algorithms with random sparsity. The number and position of the active users in each block $x^{[i]}$ are the same. The specific block sparsity representation method is shown in Fig. 1. For example, we assume that the number of blocks is 3 and the number of active users is 9. Each block is represented as $x^{[1]}$, $x^{[2]}$, $x^{[3]}$ using the proposed

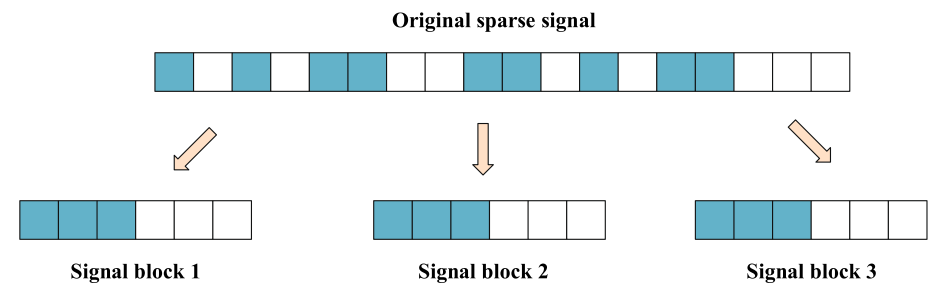

Fig. 1 The block sparse representation method

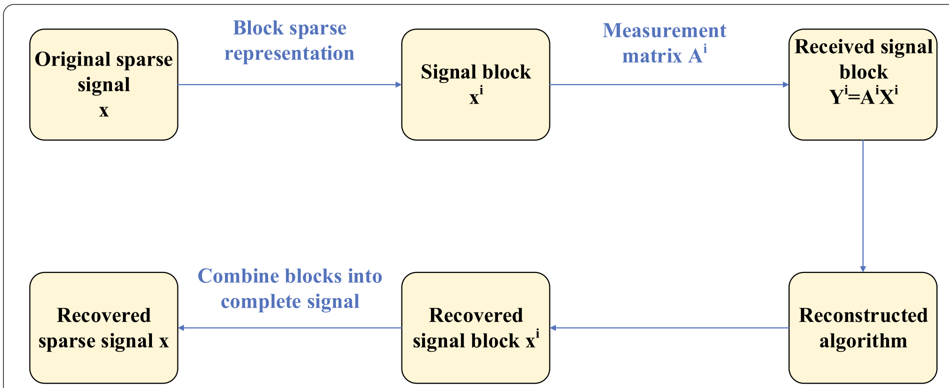

Fig. 2 The execution process of the proposed algorithm

algorithm. The entire process is depicted in the Fig. 2. As shown in the figure, x is the original sparse signal and $\hat{x}$ is the recovered sparse signal. By comparing x and $\hat{x}$, the BER performance of the proposed method is obtained.

We define G_{x^i} as the index set of non-zero elements of the ith block, whose relationship can be expressed as

$$G_{x^{[1]}} = G_{x^{[2]}} = G_{x^{[3]}} = \cdots = G_{x^{[d]}} \tag{11}$$

$$\left\|x^{[1]}\right\|_2 = \left\|x^{[2]}\right\|_2 = \left\|x^{[3]}\right\|_2 = \cdots = \left\|x^{[d]}\right\|_2 \tag{12}$$

where $||x^{[i]}||_2$ indicates the L_2 norm of $x^{[i]}$, which represents the number of non-zero elements. In this letter, the compressed sensing reconstruction algorithm we use is ISD algorithm, so $G_{x^{[i]}}$ can be represented as support set $supp(x^{[i]})$. According to (7), channel matrix $A^{[i]}$ have an influence on signal received by the station $y^{[i]}$, so it's significant to choose the proper channel matrix. In the theory of compressed sensing, the measurement matrix have to satisfy the the Restricted Isometry Property (RIP). In general, Gaussian random matrix or Bernoulli random matrix is used as the measurement matrix in some papers, and we consider using the circulant matrix as the measurement matrix to reduce computational complexity and save storage space by utilizing the previously proposed block sparse structure. According to (9), the steps to generate a block circulant matrix are listed as follows.

(1) Channel matrix $A^{[i]}$ can be divided into K/d sub-channel matrices, whose elements are composed of 0 and 1 with generation probability of 1/2 respectively. The first sub-channel matrix of length M/d is set to $A_1^{[i]}$.
(2) Move all elements of the matrix $A_1^{[i]}$ by one place to generate the second matrix $A_2^{[i]}$. Then move all elements of $A_2^{[i]}$ by one place to generate the third matrix $A_3^{[i]}$, and all sub-channel matrices are generated in turn like this.
(3) Combine all sub-channel matrices to get a complete measurement matrix $A^{[i]}$. The specific circulant matrix structure is as follows.

$$A^{[i]} = \begin{bmatrix} g_{11}^{[i]} & g_{12}^{[i]} & \cdots & g_{1\frac{M}{d}}^{[i]} \\ g_{1\frac{M}{d}}^{[i]} & g_{11}^{[i]} & \cdots & g_{1(\frac{M}{d}-1)}^{[i]} \\ \cdots & \cdots & \cdots & \cdots \\ g_{1(\frac{M}{d}-\frac{K}{d}+2)}^{[i]} & g_{1(\frac{M}{d}-\frac{K}{d}+3)}^{[i]} & \cdots & g_{1(\frac{M}{d}-\frac{K}{d}+1)}^{[i]} \end{bmatrix} \tag{13}$$

where $A^{[i]}$ contains only 0 and 1. This structure greatly simplifies the measurement matrix, makes use of the characteristic of block sparsity and also satisfies the RIP. The experimental results prove that it contributes to improving recovery accuracy. However, it can only ensure that the signal is reconstructed with a high probability by using circulant matrix or other measurement matrices for compressed sensing. For a certain reconstruction algorithm, whether there is a measurement matrix that can perfectly recover the original signal is still a problem to be studied.

The reconstruction algorithm used in this letter is ISD algorithm, which is different from traditional greedy algorithm such as OMP algorithm in support set detection. For instance, the index set of ISD algorithm will be updated after each iteration, while the index set of the greedy algorithm will remain unchanged or continue to grow. Therefore, ISD algorithm can reconstruct the original signal more accurately than the greedy algorithm. Compared with the traditional ISD algorithm, the block sparse ISD algorithm proposed in this letter expresses the original sparse signal x as $x^{[1]}, x^{[2]}, \ldots, x^{[d]}$, which reduces the algorithm complexity and shortens the signal reconstruction time. Recently, a new SISD algorithm exploiting the structured sparsity is proposed, which improves ISD algorithm by recovering multiple sparse signals in J continuous time slots in a joint manner. And the BER will decrease with the increase of time slots. Whereas, only when the number of time slots J is very large can the performance of algorithm be significantly improved, which increase the algorithm complexity. When the number of time slots is small, the performance of SISD algorithm is similar to the traditional ISD algorithm, which shows that it has limitations. On the contrary, our proposed method can recover signal accurately by fully taking advantage of block sparsity among multiple related blocks even when there are few blocks. In summary, the proposed algorithm performs better than SISD algorithm under low complexity condition. Finally, we give the specific steps of block sparse ISD algorithm in Algorithm 1. The detailed steps can be described as follows.

Before the iteration starts, the original sparse signal x is represented as d signal blocks by the proposed method: $x^{[1]}, x^{[2]}, x^{[3]}, \ldots, x^{[d]}$, and then multiply the signal block $x^{[r]}$ by the corresponding channel sensing matrix $A^{[r]}$ to obtain the received signal $y^{[r]}$. Next, ISD algorithm is used to recover the received signal $y^{[r]}$ into $\hat{x}^{[r]}$, and then combine all signal blocks $\hat{x}^{[r]}$ into recovered sparse signal $\hat{x}$. And recovery process can be expressed as the following steps.

Algorithm 1 Proposed ISD Algorithm

Require: original sparse signal x is represented as block sparse signal $x^{[1]}, x^{[2]}, ..., x^{[d]}$ by the proposed method.
Received signals: $y^{[1]} = A^{[1]}x^{[1]}, y^{[2]} = A^{[2]}x^{[2]}, y^{[3]} = A^{[3]}x^{[3]}, ..., y^{[d]} = A^{[d]}x^{[d]}$;
Channel sensing matrices: $A^{[1]}, A^{[2]}, A^{[3]}, ..., A^{[d]}$;
Channel noise matrices: $v^{[1]}, v^{[2]}, v^{[3]}, ..., v^{[d]}$;
Ensure: Recovered sparse signals:
$\hat{x} = \left[(x^{[1]})^T \ (x^{[2]})^T \ (x^{[3]})^T \ ... \ (x^{[d]})^T\right]^T$.
1: **for** r=1 to d **do**
2: $l = 0, I^{(0)} = \varnothing, T^{(0)} = (I^{(0)})^C := \{1, 2, ..., M\}$
3: **while** $\mathrm{Card}(I^{(l)}) < M - K$ **do**
4: $x^{[r](l)} = \arg\min \sum_{i \in T^{(l)}} |x_i^{[r]}|$
$\text{s.t.} A^{[r]}x^{[r]} + v^{[r]} = y^{[r]}$
5: $G^{(l)} = \mathrm{sort}(|x^{[r](l)}|)$,
$|g_{i+1}^{(l)}| - |g_i^{(l)}| > \tau^{(l)}$,
$i = \min_i |g_{i+1}^{(l)}| - |g_i^{(l)}|$,
$\epsilon^{(l)} = |g_i^{(l)}|$,
$I^{(l+1)} = \left\{i : |x_i^{(l)}| > \epsilon^{(l)}\right\}$
6: $T^{(l+1)} = \left(I^{(l+1)}\right)^C := \{1, 2, ..., M\} \backslash I^{(l+1)}$
7: $l = l + 1$.
8: **end while**
9: **return** $x^{[r]} = x^{[r](l)}, r = 1, 2, ..., d$.
10: **end for**
11: $\hat{x} = \left[(x^{[1]})^T \ (x^{[2]})^T \ (x^{[3]})^T \ ... \ (x^{[d]})^T\right]^T$

(*Step* 2) Set support set $I^{(0)} = \varnothing$, and calculate the complement set $T^{(0)} = (I^{(0)})^C$.

(*Step* 4) Obtain the rth signal block $x^{[r](l)}$ from the truncated weighted BP model in the lth iteration.

(*Step* 5) Set proper threshold $\epsilon^{(l)}$. First, the components of $x^{[r](l)}$ are sorted from small to large according to the absolute value to obtain a new signal block $G^{(l)}$. Then subtract the absolute value of the previous element $|g_i^{(l)}|$ from the absolute value of the latter element $|g_{i+1}^{(l)}|$ in $G^{(l)}$. And $\tau^{(l)}$ is given preliminarily according to the paper [14, 15]. Then we find the minimum i value of the of the adjacent components satisfying the condition: $|g_{i+1}^{(l)}| - |g_i^{(l)}| > \tau^{(l)}$ and the component $|g_i^{(l)}|$ corresponding to the minimum i is the threshold $\epsilon^{(l)}$. That is, when there is a big jump in the absolute value of two adjacent components for the first time, the smaller component is selected as the threshold. Then we detect support set of $x^{[r](l)}$ and update a new support set $I^{(l+1)}$.

(*Step* 9) When the support set $I^{(l)}$ contains enough elements to reach the end loop condition, the recovered sparse signal block $\hat{x}^{[r]}$ is returned. And all sparse signal blocks are obtained in turn: $x^{[1]}, x^{[2]}, x^{[3]}, \ldots, x^{[d]}$.

(*Step* 11) Combine all d sparse signal blocks into the original sparse signal $\hat{x}$.

In the proposed algorithm, the threshold setting is based on the prior information that the non-zero elements of the each sparse signal block has fast degradation distribution characteristics. According to step 4, the optimization problem is the L1 minimization problem, and the true non-zero values of sparse signal $x^{[r](l)}$ are very large, but the number is small, while false non-zero values are very small, but the number is large. Therefore, it is possible that the sum of true non-zero elements is the same as the sum of false non-zero element, then true non-zero elments will be replaced by false non-zero elements in support set, which causes false detection. In this way, we can get right position of non-zero elements and determine more support set elements in the next iteration, and finally recover the complete support set.

The traditional ISD algorithm and the SISD algorithm proposed in recent years only consider the conventional sparse signal without additional structure. SISD algorithm can recover multiple sparse signals at the same time by expanding a received signal into a combination of multiple received signals in a joint manner. However, the structure of the original sparse signal is unchanged, and the position of non-zero elements is random. Different from ISD and SISD algorithm, the sparse signal in our proposed algorithm has a block sparse structure, where non-zero elements $x^{[1]}, x^{[2]}, x^{[3]}, \ldots, x^{[d]}$. As a result, each block has the same support set. By exploiting this structure, the signal blocks can be recovered in a joint manner, which not only increases the probability of signal recovery, but also improves the accuracy of signal recovery. Obviously, when $d = 1$, the signal with sparse structure degenerate into conventional sparse signal. And computational complexity mainly coming from BP problem in *Step* 4 is an indicator used to measure the performance of algorithm. And block method can reduces the scale of the received signal in a recovery process, which greatly speeds up the detection of the support set and reduces the complexity on the whole.

In the grant-free NOMA system, we apply the block sparse ISD algorithm to realize the detection of user activity. A sparse signal block can be regarded as a user group and different signal blocks correspond to different user groups. In a user group, each user communicates by using NOMA technology. And appropriate power is allocated to users who are divided into groups according to their channel conditions.

4 Results and discussion

In this section, we compare the proposed ISD algorithm with ISD and SISD algorithm for simulation results. The BER is used to evaluate the accuracy of signal recovery, and the CPU running time is used to evaluate the complexity of the algorithm. The specific simulation parameters are as follows. The total number of users is $M = 150$, the number of active users is $N = 10$, the number of subcarriers is $K = 10$, and number of blocks is $d = 2$. Hence, the number of users in a block is 75, the number of active users in a block is 5, and the number of subcarriers in a block is 50. The measurement matrix is a circulant matrix whose elements are 0 or 1. In the SISD algorithm, the number of time slots is $J = 2$, and the measurement matrix is a Gaussian random matrix.

Figure 3 shows the BER performance of block sparse ISD algorithm under different number of blocks. From the simulation results, we can know that the BER performance of proposed algorithm improves with the increase of the number of blocks, which is due to the use of block sparsity to improves the accuracy of recovery.

Figure 4 shows the BER performance of different algorithms under different SNR. The results in Fig. 4 shows that compared with ISD algorithm, the proposed block sparse ISD algorithm has 2.5dB SNR gain when BER $= 5 * 10^{-2}$. Compared with the SISD algorithm, the proposed block sparse ISD algorithm has 1.75dB SNR gain when BER $= 10^{-2}$. It shows that the proposed algorithm has lower requirements for SNR than ISD and SISD algorithm under the same BER. Figures 5 and 6 show that the performance of the

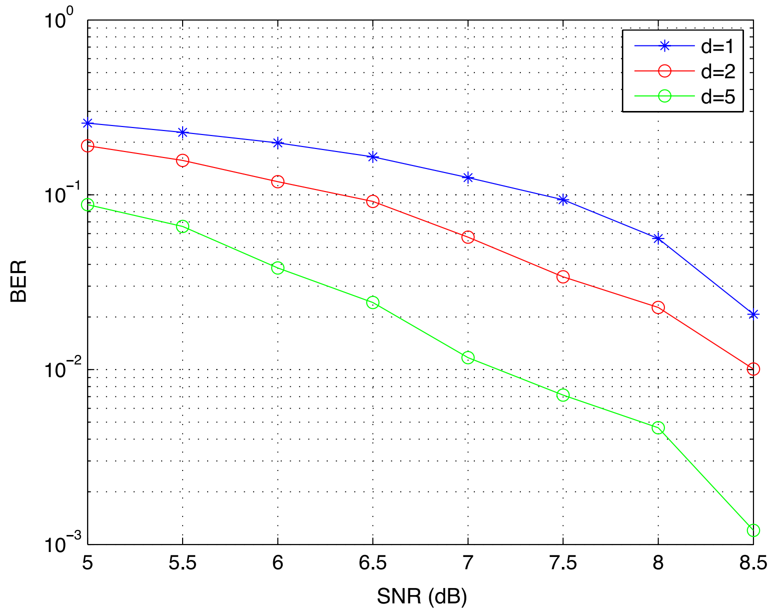

Fig. 3 BER performance comparison against SNR (dB) for $d = 1, 2, 5$, when the number of active user N is 10

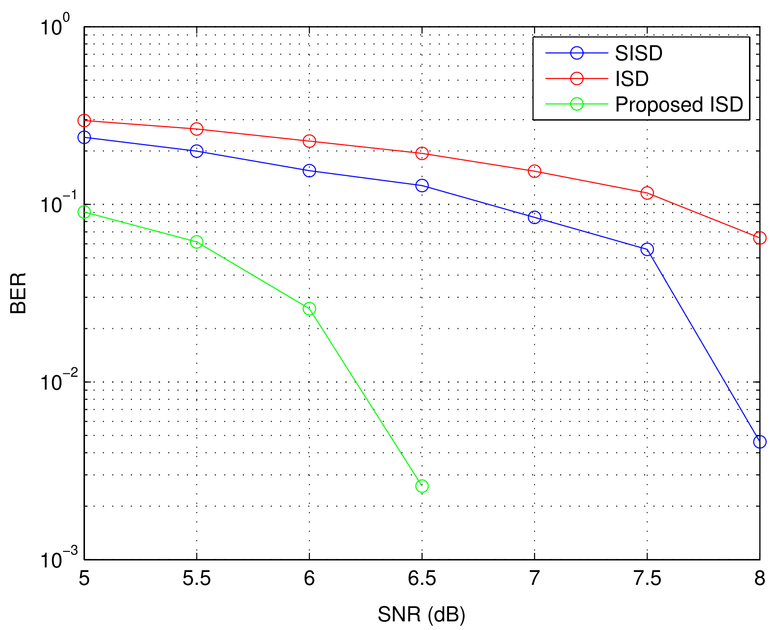

Fig. 4 BER performance comparison against SNR (dB), where the number of signal blocks is $d = 2$ and the number of continuous time slots is $J = 2$ when the number of active user N is 10

proposed algorithm is better than others in the case of higher sparsity, which shows the applicability of the algorithm.

Table 1 shows the average CPU running time for all algorithm, that is, the time required for signal recovery, which is used to evaluate the algorithm complexity. The simulation environment is MATLAB 2010b with Intel (R) Core (TM) i7-10700f, 2.90

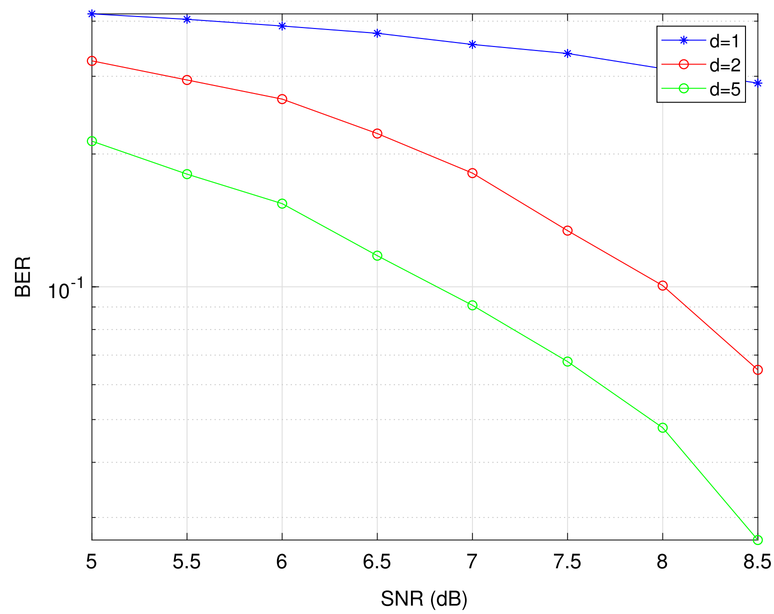

Fig. 5 BER performance comparison against SNR (dB) for $d = 1, 2, 5$ when the number of active user N is 20

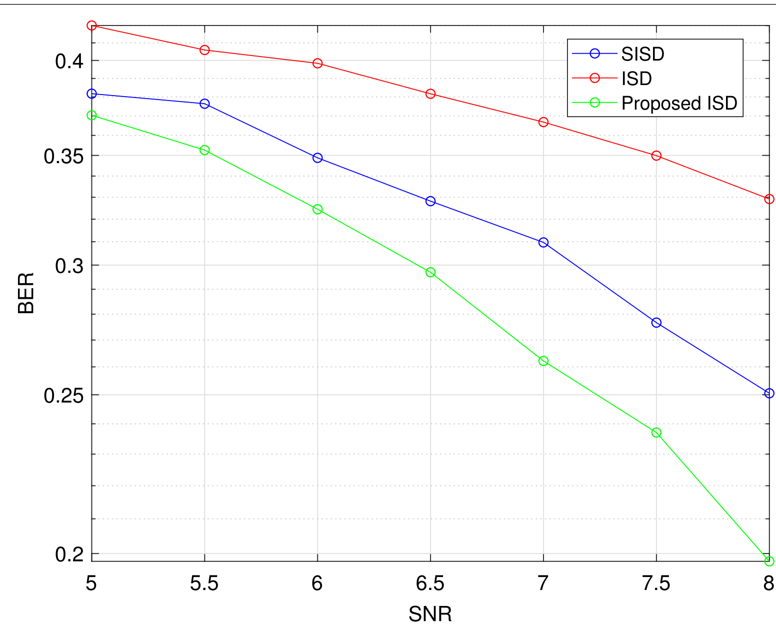

Fig. 6 BER performance comparison against SNR (dB), where the number of signal blocks is $d = 2$ and the number of continuous time slots is $J = 2$ when the number of active user N is 20

Table 1 The average CPU running time (second) for all algorithm

Time slots	Block number	The block sparse ISD algorithm	SISD	ISD
2	2	4641	8526	60064

GHz CPU with 16GB memory under Windows 10 operating system. And the simulation parameters are the same as the simulation parameters in Fig. 1. From the results in Table 1, we can see that traditional ISD algorithm has the longest running time and performance of SISD algorithm is much better than ISD algorithm. And the proposed ISD algorithm can recover the original sparse signal twice as fast as the SISD algorithm. This is because the SISD algorithm is very sensitive to the number of time slots, and its performance is not ideal when the number of time slots is low, and the increase of the number of time slots in turn increases the complexity. The proposed algorithm with an extra sparse structure performs better than ISD algorithm when the number of blocks is low. Thus, it is more suitable to apply in grant-free NOMA system with massive user connections.

5 Conclusion

This letter studies the sparse signal reconstruction problem in grant-free NOMA system for 5g. We propose a new blcok sparse method based on ISD algorithm by exploiting the sparsity of user activities in massive Machine Type Communications. Specifically, we represent the original sparse signal in blocks, and then design the channel matrix as a circulant matrix to get the received signal blocks. Then the reconstructed algorithm is used to detect the user activity and data to recover the signal blocks, which are recombined into a recovered original sparse signal. Compared with ISD algorithm and SISD algorithm, the proposed method improves the traditional ISD algorithm with the extra block sparse structure, and the support set of each block is the same. The circulant matrix is selected as the measurement metrix. The simulation results show that the proposed algorithm can achieve 1.75dB SNR gain compared with SISD algorithm and achieve 2.5dB SNR gain compared with ISD algorithm. From the perspective of algorithm complexity, the signal recovery time of SISD algorithm is one tenth of that of ISD algorithm and half of that of SISD algorithm, which indicates that the proposed algorithm is very efficient. Therefore, the block sparse ISD algorithm has more performance gains than other ISD algorithms, and it is suitable to apply in the NOMA system. Finally, it is worth discussing that the sparsity of sparse signal is relatively low in this paper. A promising research direction is to achieve accurate recovery of a sparse signal with high sparsity. In the future, whether we can achieve accurate recovery by using block ISD algorithm for a sparse signal with higher sparsity remains to be studied.

Abbreviations
NOMA: Non-orthogonal multiple access; IoV: Internet of Vehicles; mMTC: Massive machine type communication.

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Authors' contributions
Both authors have contributed toward this work as well as in compilation of this manuscript. All authors read and approved the final manuscript.

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Availability of data and materials
Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

Declarations

Competing interests
The authors declare that they have no competing interests.

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References
1. L. Dai, B. Wang, Y. Yuan, S. Han, I. Chih-lin, Z. Wang, Non-orthogonal multiple access for 5G: solutions, challenges, opportunities, and future research trends. IEEE Commun. Mag. **53**(9), 74–81 (2015)
2. S.K. Sharma, X. Wang, Toward massive machine type communications in ultra-dense cellular IoT networks: Current issues and machine learning-assisted solutions. IEEE Commun. Surv. Tutor. **22**(1), 426–471 (2020)
3. L. Liu, E.G. Larsson, W. Yu, P. Popovski, C. Stefanovic, E. de Carvalho, Sparse signal processing for grant-free massive connectivity: a future paradigm for random access protocols in the Internet of Things. IEEE Signal Process. Mag. **35**(5), 88–99 (2018)
4. Q. Li, J. Ma, G. Erlebacher, A new reweighted algorithm with support detection for compressed sensing. IEEE Signal Process. Lett. **19**(7), 419–422 (2012)
5. J.A. Tropp, A.C. Gilbert, Signal recovery from random measurements via orthogonal matching pursuit. IEEE Trans. Inf. Theory **53**(12), 4655–4666 (2007)
6. B. Wang, L. Dai, T. Mir, Z. Wang, Joint user activity and data detection based on structured compressive sensing for NOMA. IEEE Commun. Lett. **20**(7), 1473–1476 (2016)
7. A.T. Abebe, C.G. Kang, Iterative order recursive least square estimation for exploiting frame-wise sparsity in compressive sensing-based MTC. IEEE Commun. Lett. **20**(5), 1018–1021 (2016)
8. X. Liu, X. Zhang, Rate and energy efficiency improvements for 5G-based IoT with simultaneous transfer. IEEE Internet Things J. **6**(4), 5971–5980 (2019)
9. M.F. Duarte, Y.C. Eldar, Structured compressed sensing: from theory to applications. IEEE Trans. Signal Process. **59**(9), 4053–4085 (2011)
10. N. Wang, D. Chen, J. Chen, X. Xu and J. Wan, Clustering data gathering method based on compressed sensing in wireless sensor networks, in *2018 10th International Conference on Intelligent Human-Machine Systems and Cybernetics (IHMSC)*, pp. 214–217 (2018)
11. S.M.R. Islam, N. Avazov, O.A. Dobre, K. Kwak, Power-domain non-orthogonal multiple access (NOMA) in 5G systems: potentials and challenges. IEEE Commun. Surv. Tutor. **19**(2), 721–742 (2017)
12. X. Liu, X. Zhang, M. Jia et al., 5G-based green broadband communication system design with simultaneous wireless information and power transfer. Phys. Commun. **28**, 130–137 (2018)
13. B. Shim, B. Song, Multiuser detection via compressive sensing. IEEE Commun. Lett. **16**(7), 972–974 (2012)
14. Y. Wang, W. Yin, Sparse signal reconstruction via iterative support detection. SIAM J. Imag. Sci. **3**(3), 462–491 (2010)
15. F. Li, K. Lam, X. Liu, J. Wang, K. Zhao, L. Wang, Joint pricing and power allocation for multibeam satellite systems with dynamic game model. IEEE Trans. Veh. Technol. **67**(3), 2398–2408 (2018)

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