# Compressive Multi-User Detector for Spatial Modulation (SM)-Based Random Access in Internet of Things (IoTs)

Zhen Gao

Advanced Research Institute for Multidisciplinary Science (ARIMS) & School of Information and Electronics
Beijing Institute of Technology, Beijing 100081, P. R. China
Email: gaozhen010375@foxmail.com

***Abstract*—For the emerging Internet of Things (IoTs), one challenge is how to support massive connectivity with high spectrum efficiency (SE) and energy efficiency (EE). Against this background, we propose that each user equipment (UE) with multiple low-cost antennas but only one power-hungry radio frequency (RF) chain exploits spatial modulation (SM) to randomly access the network, where SM is used to enhance both the uplink SE and EE. However, due to massive multi-antenna UEs while the limited number of base station (BS) antennas, how to realize the reliable random access for massive connectivity is challenging. Fortunately, the access in IoTs exhibits the sporadic machine-type communication (MTC), which indicates the unchanged sparsity of active UEs in several successive time slots. Moreover, SM signals also exhibit the sparsity due to only one RF chain but multiple antennas for each UE. By leveraging these sparse features of random access signals, we propose a compressive sensing (CS)-based multi-user detector (MUD), which can reliably support massive random access. Simulation results also verify the good performance of our proposed scheme.**

***Index Terms*—Compressive sensing (CS), random access, machine-type communication (MTC), Internet of Things (IoT), spatial modulation (SM), multi-user detector (MUD)**

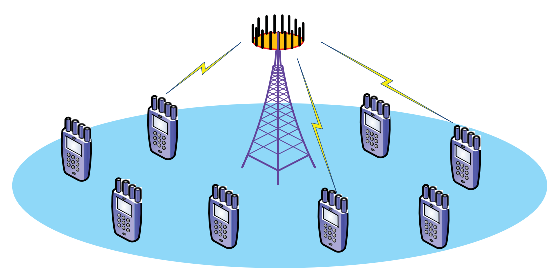

Fig. 1. This paper proposes the SM-based random access for IoTs, where the proportion of active UEs in each time slot is small due to sporadic MTC.

## I. Introduction

The emerging Internet of Things (IoTs) enables massive physical objects to access Internet and exchange information, and it has been reshaping and will have a significant impact on human life [1]. In IoTs, it is expected that the machine-type communication (MRT) will grow exponentially, and thousands of UEs per square kilometer will be connected to the network [2], [3]. As a consequence, how to effectively support massive connectivity with high spectrum efficiency (SE) and high energy efficiency (EE) is desired [1].

To achieve both high SE and EE for such massive connectivity in IoTs, as shown in Fig. 1, we propose the s-patial modulation (SM)-based uplink random access [4]. To be specific, each user equipment (UE) employing multiple antennas but only one radio frequency (RF) chain adopts SM for the uplink access, while the base station (BS) equipped with multiple antennas serves massive connectivity. Clearly, due to extra spatial degree of freedom derived from multiple antennas at each UE, SM can be used to improve the uplink throughput [4]. Moreover, due to multiple low-cost antennas but only one power-hungry and high-cost RF chain for each UE, such an uplink access scheme also enjoys high EE [4].

On the other hand, for IoTs with ultra-dense UEs per square kilometer, due to massive UEs with multiple antennas while the limited number of antennas at the BS, how to reliably support massive connectivity can be challenging. Fortunately, experiments and theoretical analysis have shown that the uplink access in IoTs appear to have the sporadic MTC [2], [3]. That is to say, although the number of UEs in the network can be large, the number of simultaneously active UEs can be small. Such small proportion of active UEs compared to the large number of total UEs indicates the sparsity of active UEs. Moreover, the sparse pattern further remains unchanged in several successive time slots, since more than one time slots will be used for uplink access. Additionally, due to the much smaller number of RF chains than that of antennas at the UEs, the random access SM signals also have the sparsity. By leveraging these sparse features of random access signals, we propose a compressive sensing (CS)-based multi-user detector (MUD), which can achieve the reliable detection performance at the BS. Simulation results also verify the good performance of the proposed scheme.

Throughout our discussions, the boldface lower and upper-case symbols denote column vectors and matrices, respectively. The Moore-Penrose inversion, transpose, and conjugate transpose operators are given by $(\cdot)^\dagger$, $(\cdot)^{\mathrm{T}}$ and $(\cdot)^*$, respectively. The $\ell_2$-norm is given by $\|\cdot\|_2$, and $|\Gamma|_c$ is the cardinality of the set $\Gamma$, and $\Gamma(m)$ denotes the $m$-th element of $\Gamma$. The support set of the vector $\mathbf{a}$ is denoted by $\mathrm{supp}\{\mathbf{a}\}$. $\mathbf{a}|_\Gamma$ denotes the entries of $\mathbf{a}$ whose indices are defined by $\Gamma$, while $\mathbf{A}|_\Gamma$

denotes a sub-matrix of $\mathbf{A}$ with column indices defined by $\Gamma$. $[\mathbf{a}]_i$ denotes the $i$-th entry of the vector $\mathbf{a}$.

## II. Proposed CS-Based MUD

We consider the BS employing $M$ antennas can serve $N$ UEs, where each UE is equipped with $n_t > 1$ antennas but only 1 RF chain, and SM is exploited for the uplink access. Moreover, $N$ UEs adopt random access to connect the network. In the $t$-th time slot, the received random access signal can be expressed as

$$\mathbf{r}^{(t)} = \sum_{n=1}^{N} \mathbf{H}_n^{(t)} \mathbf{s}_n^{(t)} + \mathbf{w}^{(t)} = \tilde{\mathbf{H}}^{(t)} \tilde{\mathbf{s}}^{(t)} + \mathbf{w}^{(t)}, \tag{1}$$

where $\mathbf{r}^{(t)} \in \mathbb{C}^{M\times 1}$, $\mathbf{H}_n^{(t)} \in \mathbb{C}^{M\times n_t}$ is the MIMO channel matrix associated with the $n$-th UE in the $t$-th time slot, $\mathbf{s}_n^{(t)} \in \mathbb{C}^{n_t\times 1}$ is the $n$-th UE's SM signal, $\mathbf{w}^{(t)} \in C^{M\times 1}$ is additive white Gaussian noise (AWGN) at the BS, $\tilde{\mathbf{H}}^{(t)} = \left[\mathbf{H}_1^{(t)}, \mathbf{H}_2^{(t)}, \cdots, \mathbf{H}_N^{(t)}\right] \in \mathbb{C}^{M\times (Nn_t)}$ is the aggregate MIMO channel matrix, and $\tilde{\mathbf{s}}^{(t)} = \left[\left(\mathbf{s}_1^{(t)}\right)^{\mathrm{T}}, \left(\mathbf{s}_2^{(t)}\right)^{\mathrm{T}}, \cdots, \left(\mathbf{s}_N^{(t)}\right)^{\mathrm{T}}\right]^{\mathrm{T}} \in \mathbb{C}^{(Nn_t)\times 1}$ is the aggregate SM signal.

Due to the large $Nn_t$ but limited $M$, the uplink multi-user detection problem (1) can be a challenging large-scale under-determined problem. Typically, conventional detectors require $M \geq Nn_t$ for reliable detection [4]. Thanks to the sporadic MTC in IoTs, the number of simultaneously active UEs $N_a \ll N$. In this way, (1) can be further written as

$$\begin{aligned}\mathbf{r}^{(t)} &= \sum_{n\in\Omega^{(t)}} \mathbf{H}_n^{(t)} \mathbf{s}_n^{(t)} + \sum_{n\notin\Omega^{(t)}} \mathbf{H}_n^{(t)} \mathbf{s}_n^{(t)} + \mathbf{w}^{(t)} \\ &= \sum_{n\in\Omega^{(t)}} \mathbf{H}_n^{(t)} \mathbf{s}_n^{(t)} + \mathbf{w}^{(t)} = \bar{\mathbf{H}}^{(t)} \bar{\mathbf{s}}^{(t)} + \mathbf{w}^{(t)},\end{aligned} \tag{2}$$

where $\Omega^{(t)}$ is the index set of active UEs in the $t$-th time slot, $N_a = \left|\Omega^{(t)}\right|_c \ll N$, $\mathbf{s}_n^{(t)} = \mathbf{0}$ for $n \notin \Omega^{(t)}$, and $\bar{\mathbf{H}}^{(t)} = \left[\mathbf{H}_{\Omega^{(t)}(1)}^{(t)}, \mathbf{H}_{\Omega^{(t)}(2)}^{(t)}, \cdots, \mathbf{H}_{\Omega^{(t)}(N_a)}^{(t)}\right]$ and $\bar{\mathbf{s}}^{(t)} = \left[\left(\mathbf{s}_{\Omega^{(t)}(1)}^{(t)}\right)^{\mathrm{T}}, \left(\mathbf{s}_{\Omega^{(t)}(2)}^{(t)}\right)^{\mathrm{T}}, \cdots, \left(\mathbf{s}_{\Omega^{(t)}(N_a)}^{(t)}\right)^{\mathrm{T}}\right]^{\mathrm{T}}$ are the aggregate MIMO channel matrix and aggregate SM signal associated with active UEs, respectively. Such sparisty of active UEs motivates us to exploit CS theory to detect the indices of active UEs $\Omega^{(t)}$ and the associated SM signals $\mathbf{s}_n^{(t)}$ for $n \in \Omega^{(t)}$ with $M \ll Nn_t$.

Moreover, since each UE's access signal will be transmitted in multiple successive time slots, the sparsity of active UEs can be considered to be unchanged in $J > 1$ time slots, i.e.,

$$\Omega^{(1)} = \Omega^{(2)} \cdots = \Omega^{(t)} = \cdots = \Omega^{(J)} = \Omega, 1 \le t \le J. \tag{3}$$

Note that we consider $\{\mathbf{H}_n^{(t)}\}_{t=1}^J$, $\forall n$ are quasi-static due to the temporal channel correlation, i.e., $\mathbf{H}_n^{(t)} = \mathbf{H}_n$ [6].

Additionally, since each UE equipped with $n_t$ antennas and only one RF chain adopts SM to access the network, their SM signals have the sparsity level of one, i.e., $\left|\mathrm{supp}\left(\mathbf{s}_n^{(t)}\right)\right|_c = 1$ for $n \in \Omega$, and thus $\left|\mathrm{supp}\left(\bar{\mathbf{s}}^{(t)}\right)\right|_c = N_a$, where $\left[\mathbf{s}_n^{(t)}\right]_{\Gamma_n^{(t)}} \in \mathbb{Q}$, $\Gamma_n^{(t)} = \mathrm{supp}\left(\mathbf{s}_n^{(t)}\right)$ for $n \in \Omega$, and $\mathbb{Q}$ is the constellation set such as $Q$-QAM with the order of $Q = |\mathbb{Q}|_c$.

---

**Algorithm 1** Proposed CS-based MUD.

---

**Input:** Received signal $\mathbf{r}^{(t)}$, the channel matrices $\{\mathbf{H}_n\}_{n=1}^N$, where $1 \le t \le J$.

**Output:** Estimate of active UEs' index set $\hat{\Omega}$ and associated SM signals $\hat{\mathbf{s}}_n^{(t)}$ for $n \in \hat{\Omega}$.

1: $\mathbf{z}^{(t)} = \mathbf{r}^{(t)}, \forall t$;
2: $\Theta_0^{(t)} = \emptyset, \forall t$;
3: $k = 1$;
4: **repeat**
5: $\quad \mathbf{a}_n^{(t)} = (\mathbf{H}_n)^* \mathbf{z}^{(t)}, \forall t, n$;
6: $\quad \tau_{n,t} = \arg\max_{\tilde{\tau}_{n,t}} \left|\left[\mathbf{a}_n^{(t)}\right]_{\tilde{\tau}_{n,t}}\right|^2, \forall t, n$;
7: $\quad \Gamma = \arg\max_{\tilde{\Gamma}} \left\{ \sum_{n\in\tilde{\Gamma}} \sum_{t=1}^{J} \left|\left[\mathbf{a}_n^{(t)}\right]_{\tau_{n,t}}\right|^2, \left|\tilde{\Gamma}\right|_c = N_a \right\}$;
8: $\quad \Theta^{(t)} = \left\{(\Gamma(m) - 1)n_t + \tau_{\Gamma(m),t}\right\}_{m=1}^{N_a}, \forall t$;
9: $\quad \mathbf{b}^{(t)}\Big|_{\Theta_{k-1}^{(t)} \cup \Theta^{(t)}} = \left(\tilde{\mathbf{H}}^{(t)}\Big|_{\Theta_{k-1}^{(t)} \cup \Theta^{(t)}}\right)^{\dagger} \mathbf{r}^{(t)}, \forall t$;
10: $\quad \Theta_k^{(t)} = \arg\max_{\tilde{\Theta}_k^{(t)}} \left\{ \sum_{n\in\tilde{\Theta}_k^{(t)}} \sum_{t=1}^{J} \left\|\mathbf{b}_n^{(t)}\right\|_2^2, \left|\tilde{\Theta}_k^{(t)}\right|_c = N_a \right\}, \forall t$;
11: $\quad \mathbf{c}^{(t)}\Big|_{\Theta_t^{(t)}} = \left(\tilde{\mathbf{H}}^{(t)}\Big|_{\Theta_t^{(t)}}\right)^{\dagger} \mathbf{r}^{(t)}, \forall t$;
12: $\quad \mathbf{z}^{(t)} = \mathbf{r}^{(t)} - \tilde{\mathbf{H}}^{(t)} \mathbf{c}^{(t)}, \forall t$;
13: $\quad k = k + 1$;
14: **until** $\Theta_{k-1}^{(t)} = \Theta_k^{(t)}, \forall t$
15: $\hat{\Omega} = \Gamma, \hat{\mathbf{s}}_n^{(t)} = \mathbf{c}_n^{(t)}$;

---

By exploiting these sparse features, we propose a CS-based MUD to solve the challenging massive random access. The proposed CS-based MUD can be illustrated in Algorithm 1, which is developed from the classical subspace pursuit (SP) algorithm [5]. Specifically, in Algorithm 1, lines 1∼3 define the initial residual, support set, and iteration index, respectively. The loop including lines 4∼14 stops when $\Theta_{k-1}^{(t)} = \Theta_k^{(t)}, \forall t$. In each iteration, line 6 identifies the index of each UE's potential active antenna according to correlation operation in line 5; line 7 identifies the indices of potential active UEs; line 8 obtains preliminary support set; line 9 estimates the constellation symbols according to the preliminary support set using least squares (LS); line 10 prunes the support set by selecting the $N_a$-best support set; line 11 re-estimates the constellation symbols according to the pruning support set using LS; line 12 computes the residual; line 13 updates the iteration index. Finally, after the iteration stops, line 15 obtains the estimation of active UEs' indices and the associated random access SM signals. Note that in Algorithm 1, $\mathbf{b}^{(t)} = \left[\left(\mathbf{b}_1^{(t)}\right)^{\mathrm{T}}, \left(\mathbf{b}_2^{(t)}\right)^{\mathrm{T}}, \cdots, \left(\mathbf{b}_N^{(t)}\right)^{\mathrm{T}}\right]^{\mathrm{T}} \in \mathbb{C}^{Nn_t\times 1}, \forall t$ with $\mathbf{b}_n^{(t)} \in \mathbb{C}^{n_t\times 1}, \forall t, n$ and $\mathbf{c}^{(t)} = \left[\left(\mathbf{c}_1^{(t)}\right)^{\mathrm{T}}, \left(\mathbf{c}_2^{(t)}\right)^{\mathrm{T}}, \cdots, \left(\mathbf{c}_N^{(t)}\right)^{\mathrm{T}}\right]^{\mathrm{T}} \in \mathbb{C}^{Nn_t\times 1}, \forall t$ with $\mathbf{c}_n^{(t)} \in \mathbb{C}^{n_t\times 1}, \forall t, n$.

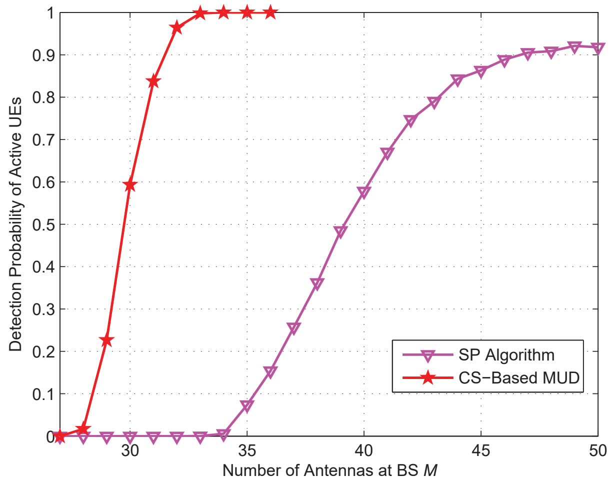


Fig. 2. Comparison of detection probabilities of active UEs achieved by conventional SP algorithm and proposed CS-based MUD versus the number of BS antennas $M$.

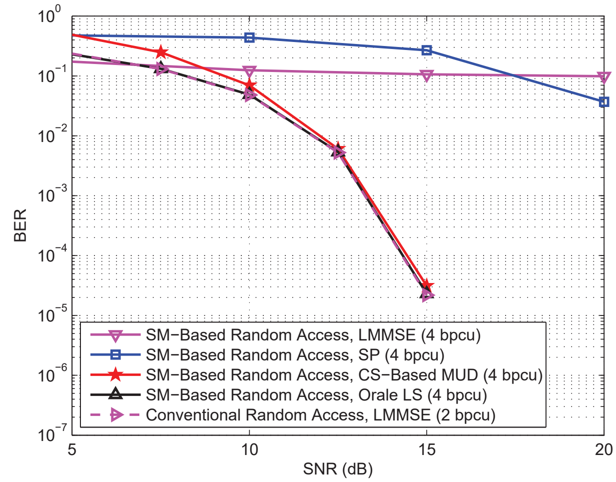


Fig. 3. The BERs achieved by different detectors against different SNR's in the proposed SM-based random access scheme and conventional random access scheme.

## III. Simulation Results

A simulation study is carried out to investigate the performance of the proposed SM-based random access scheme and the associated CS-based MUD. In simulations, we consider $n_t = 4$, $N = 128$, $N_a = 16$, $J = 10$, and QPSK constellation set is adopted. Moreover, we provide the performance of conventional linear minimum mean square error (LMMSE)-based detector [4] and the SP-based detector [5]. The oracle LS estimator with the priori information of indices of active UEs and indices of their active antennas for SM is also plotted as the comparison benchmark.

Fig. 2 compares the detection probabilities of active UEs achieved by conventional SP algorithm and proposed CS-based MUD versus the number of BS antennas $M$ in noiseless scenario. Clearly, our proposed CS-based MUD outperforms conventional SP algorithm. The good performance of our proposed detector lies in two folds. First, the proposed CS-based MUD leverages the structured sparsity of active UEs in multiple successive time slots as shown in (3). Second, we further exploit the sparsity of SM signals. Specifically, due to only one RF chain for each UE, each active UE's SM signal has the sparsity level of one, i.e., $\left|\text{supp}\left(\mathbf{s}_n^{(t)}\right)\right|_c = 1$ for $n \in \Omega$, and thus the aggregate SM signal $\bar{\mathbf{s}}^{(t)}$ has has the sparsity level of $N_a$.

Fig. 3 compares the bit-error-rate (BER) performance achieved by different detectors against different SNRs in the proposed SM-based random access scheme and conventional random access scheme, where $M = 64$. For the conventional random access scheme, each UE has one antenna and one RF chain without using SM [3]. It can be observed that the superior performance of the proposed CS-based MUD to the conventional LMMSE-based and SP-based signal detectors is clear. Moreover, the performance gap between the oracle LS detector and the proposed CS-based MUD is less than 0.1 dB. It should be pointed out that the oracle LS detector has the priori information of active UEs' indices and their active antennas' indices. Finally, compared with the conventional random access scheme with 2 bit per channel use (bpcu) due to QPSK for each UE, the proposed SM-based access scheme with 4 bpcu (QPSK can carry 2 bits and the pattern of active antenna can carry 2 bits) only suffers from a negligible BER loss. Hence, the high SE of the proposed SM-based random access scheme is self-evident.

## IV. Conclusions

This paper investigates the challenging massive random access for the emerging IoTs. The contribution of this paper lies in two folds. First, we propose an SM-based uplink random access scheme. In this scheme, each UE equipped with multiple low-cost antennas but only one power-hungry RF chain adopts SM to randomly access the network. Second, we propose a CS-based MUD at the BS. By exploiting the unchanged sparsity of active UEs in multiple time slots and the inherent sparsity of SM signals, the proposed scheme can achieve reliable multi-user detection performance. Simulation results also confirm the good performance of our proposed scheme.

## References


[1] A. Zanella, N. Bui, A. Castellani, and L. Vangelista, "Internet of Things for smart cities," *IEEE Internet Things J.*, vol. 1, no. 1, pp. 22-32, Feb. 2014.

[2] A. T. Abebe and C. G. Kang, "Compressive sensing-based random access with multiple-sequence spreading for MTC," in *Proc. IEEE Globecom'15*, Dec. 2015.

[3] A. T. Abebe and C. G. Kang, "Iterative order recursive least square estimation for exploiting frame-wise sparsity in compressive sensing-based MTC," to appear in *IEEE Commun. Lett.* 2016.

[4] P. Yang, M. Di Renzo, Y. Xiao, S. Li, and L. Hanzo, "Design guidelines for spatial modulation," *IEEE Commun. Surveys Tuts.*, vol. 17, no. 1, pp. 6-26, 2015.

[5] W. Dai and O. Milenkovic, "Subspace pursuit for compressive sensing signal reconstruction," *IEEE Trans. Inf. Theory*, vol. 55, no. 5, pp. 2230–2249, May 2009.

[6] Z. Gao, L. Dai, Z. Wang, and S. Chen, "Spatially common sparsity based adaptive channel estimation and feedback for FDD massive MIMO," *IEEE Trans. Signal Process.*, vol. 63, no. 23, pp. 6169-6183, Dec. 2015.