Joint Device Identification and Data Detection in Physical Layer for Many Devices in IoT

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***Abstract*—In this paper, we consider sparse index multiple access (SIMA) for uplink transmissions in a wireless system of a number of devices when a fraction of them are active. This multiple access scheme is suitable for the case that an access point (AP) needs to not only receive signals, but also identify active devices when there are a number of devices with unique identification sequences (the number of devices can be easily more than a million). We propose a two-stage transmission scheme and derive computationally efficient methods to estimate the channels of active devices in the first stage and to perform device identification within the physical layer together with data detection in the second stage using a well-known sparse signal estimation method in compressive sensing (CS).**

***Index Terms*—sparsity, index modulation, compressive sensing, Internet of things**

I. Introduction

Internet of things (IoT) has attracted a great deal of attention and has been studied for standardization [1], where IoT is layered into application, service support and application support, network, and device layers. In [2] and [3], code division multiple access (CDMA) and time reversal multiple access (TDMA) are considered, respectively. These two multiple access schemes are also considered for multiple access in ultra wideband (UWB) communication systems [4]. Since UWB communications are to provide short-range wireless connections for devices, various approaches for UWB might be useful for wireless IoT as demonstrated in [3].

In this paper, we study multiple access for many devices of low-data-rate applications with low activity (i.e., the number of active devices would be a fraction of the devices in a system) in a network. Due to the sparsity of active devices, various random access schemes based on the notion of compressive sensing (CS) [5], [6] have been considered in [7]–[9]. In most schemes, a device is to randomly choose a preamble or a spreading code for random access. Thus, these schemes aim at establishing connections. On the other hand, we mainly focus on simultaneous device identification and data detection in this paper under the assumption that each device uses a unique identification sequence for random access. The main advantage of this approach is that the device identification can be carried out locally within the physical layer, which can simplify the architecture of wireless sensor networks to collect big data as no central device identification is required.

To deal with the channel state information (CSI) estimation, the proposed multiple access scheme in this paper has two stages, where active devices transmit their pilot signals in the first stage to allow the AP to estimate the channels of active devices prior to data transmissions from them. In the second stage, active devices transmit data symbols based on sparse index multiple access (SIMA) [10] with unique sparse identification sequences. In this stage, the AP needs not only to identify active devices, but also to detect their data symbols. Thus, we derive an approach for the joint identification and detection using the expectation-maximization (EM) algorithm [11].

Notation: The superscripts T and H denote the transpose and complex conjugate, respectively. The p-norm of a vector $\mathbf{a}$ is denoted by $||\mathbf{a}||_p$ (If $p = 2$, the norm is denoted by $||\mathbf{a}||$ without the subscript). The superscript $\dagger$ denotes the pseudo-inverse. For a vector $\mathbf{a}$, $\mathrm{diag}(\mathbf{a})$ is the diagonal matrix with the diagonal elements from $\mathbf{a}$. For a matrix $\mathbf{X}$ (a vector $\mathbf{a}$), $[\mathbf{X}]_n$ ($[\mathbf{a}]_n$) represents the nth column (element, resp.). If n is a set of indices, $[\mathbf{X}]_n$ is a submatrix of $\mathbf{X}$ obtained by taking the corresponding columns. The Kronecker product is denoted by $\otimes$. $\mathbb{E}[\cdot]$ and $\mathrm{Var}(\cdot)$ denote the statistical expectation and variance, respectively. $\mathcal{CN}(\mathbf{a}, \mathbf{R})$ ($\mathcal{N}(\mathbf{a}, \mathbf{R})$) represents the distribution of circularly symmetric complex Gaussian (CSCG) (resp., real-valued Gaussian) random vectors with mean vector $\mathbf{a}$ and covariance matrix $\mathbf{R}$.

II. System Model

Throughout this paper, we consider a system of an AP and K devices and multicarrier uplink transmissions with L subcarriers. It is assumed that $K \gg L$, while only a fraction of devices become active to transmit their signals to the AP or gateway. For convenience, we denote by M the number of active devices and assume that $M < L$. In addition, denote by $\mathcal{A}$ the index set of active devices. Clearly, we have $|\mathcal{A}| = M$. It is also assumed that each device has a unique identification sequence for random access. Since we consider a large K (e.g., $K \geq 10^6$), there should be a sufficient number of identification sequences for devices.

This research was supported by Korea Electric Power Corporation through Korea Electrical Engineering & Science Research Institute (grant number: R15XA03-60) and the GIST Research Institute (GRI) in 2016.

A. System Model for Two-Stage Access Scheme

In this subsection, we present the system model for a two-stage uplink access scheme that is illustrated in Fig. 1. At the beginning of a slot, the AP broadcasts a synchronous (or beacon) signal. Then, in Stage I, the devices transmit uplink pilot signals to the AP so that the AP can estimate the channels for the (coherent) detection of the signals from devices at the AP. In order to have a low overhead for the channel estimation, we assume that only active devices (i.e., active devices) can send pilot signals that are chosen randomly from a codebook of pilot signals, which is pre-defined and common to all devices. Details of Stage I with the following AP's broadcast signaling will be presented in Subsection III-A.

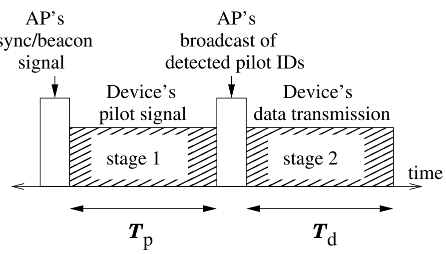

Fig. 1. An illustration of two-stage (uplink) access scheme with the AP's synchronous signal that initiates uplink access by devices.

In Stage II, active devices transmit their signals with unique identification sequences. Since the AP has CSI, it can perform coherent detection to not only detect data symbols, but also identify active devices. We devise a method for joint active device identification and data detection in Subsection III-B.

We now consider the received signal at the AP. Let $r_{l,t}$ denote the received signal at the AP through subcarrier l during time t. Then, it can be shown that

$$\mathbf{r}_t = [r_{0,t} \ \dots \ r_{L-1,t}]^\mathrm{T} = \sum_{k \in \mathcal{A}} \mathbf{H}_{k,t} \mathbf{a}_{k,t} + \mathbf{n}_t, \ t \in \mathcal{T}_\mathrm{p}, \ t \in \mathcal{T}_\mathrm{d}, \tag{1}$$

where $\mathbf{H}_{k,t}$ and $\mathbf{a}_{k,t}$ are the channel matrix and transmitted signals from device $k \in \mathcal{A}$, respectively, and $\mathbf{n}_t = [n_{0,t} \ \dots \ n_{L-1,t}]^\mathrm{T} \sim \mathcal{CN}(0, N_0 \mathbf{I})$ is the background noise. Here, $\mathcal{T}_\mathrm{p}$ and $\mathcal{T}_\mathrm{d}$ represent the sets of time indices for the pilot transmission in Stage I and the data transmission in Stage II, respectively, as shown in Fig. 1. Throughout the paper, we assume that $\mathbf{H}_{k,t} = \mathbf{H}_k, \ t \in \mathcal{T}_\mathrm{p}, \ t \in \mathcal{T}_\mathrm{d}$, which means that the time duration for Stages I and II is less than or equal to the coherence time, and $\mathbf{H}_k$ is given by $\mathbf{H}_k = \mathrm{diag}(H_{k,0}, \dots, H_{k,L-1})$, where $H_{k,l} = \sum_{i=0}^{P_k-1} h_{k,i} e^{-j\frac{2\pi i l}{L}}$. Here, $\{h_{k,i}\}$ is the (uplink) channel impulse response (CIR) from device k to the AP and P_k is the length of CIR. For convenience, we assume that $P_k = P$ for all k.

B. CDMA for Identification

For active device identification, we may consider an additional step prior to data transmissions using unicast communication for each active device as in [12]. However, in order to efficiently exploit radio resources, it would be desirable to identify active devices simultaneously (not by unicast communication). To this end, we may consider multicarrier CDMA (MC-CDMA) with a unique spreading code for each device.

In order to focus on the identification of active devices, we now assume that the AP knows the channel matrices of all devices, $\{\mathbf{H}_k\}$. Note that if the channel matrices, $\{\mathbf{H}_k\}$, are different and known to the AP, they can be used as signatures to identify active devices. However, as the channel matrices are random and vary, it may not be easy to use them as signatures. Thus, in this paper, we assume that each device has a unique sequence for identification purposes.

Let $\mathbf{c}_k$ be the unique spreading code for device k. Then, $\mathbf{a}_{k,t} = \mathbf{c}_k d_{k,t}$, where $d_{k,t} \in \mathcal{D}$ is the data symbol from device k. Here, $\mathcal{D}$ is the signal alphabet and $d_{k,t}$ is assumed to be independent. For simplicity, we assume that $\mathcal{D} = \{-1, +1\}$ (i.e., binary phase shift keying (BPSK) is used) throughput the paper. This approach is referred to as the MC-CDMA based approach. A salient feature of the MC-CDMA based approach is that the transmissions of identification sequences and data symbols of active devices can be carried out simultaneously by using a unique sequence for each device in random access. In [13], [14], the identification of active users is studied when a fraction of users are active. If the number of bits to be transmitted from active devices is not large, this approach can efficiently exploit limited radio resources. In [7], [9], exploiting the sparsity of active devices, CS-based approaches to estimate sparse signals are considered for the identification of active devices as well as the detection of their signals (in [7], the CDMA system with the sparsity of active devices is referred to as sparse CDMA).

III. Two-Stage Transmissions and CS-based Estimation and Identification

A. Stage I: Channel Estimation

Suppose that there is a codebook of D pilot spreading sequences for the uplink training to estimate the CSI of active devices, which are denoted by $\{\mathbf{p}_i, \ i = 1, \dots, D\}$. Each device can choose one of the pilot sequences in the codebook randomly. Let $i(k)$ denote the pilot spreading sequence that is chosen by device $k \in \mathcal{A}$. In addition, let $\mathbf{x} = \mathbf{r}_t, \ t \in \mathcal{T}_\mathrm{p}$, which is the received signal at the AP in Stage I. Then, we have

$$\mathbf{x} = \sum_{k \in \mathcal{A}} \mathbf{H}_k \mathbf{p}_{i(k)} + \mathbf{n}_\mathrm{p} = \sum_{k \in \mathcal{A}} \mathrm{diag}(\mathbf{p}_{i(k)}) \mathbf{F} \mathbf{h}_k + \mathbf{n}_\mathrm{p}, \tag{2}$$

where $[\mathbf{F}]_{l,p} = e^{-\frac{j2\pi l p}{L}}$, $l \in \{0, \dots, L-1\}$, $p \in \{0, \dots, P-1\}$, $\mathbf{h}_k = [h_{k,0} \ \dots \ h_{k,P-1}]^\mathrm{T}$, and $\mathbf{n}_\mathrm{p} \sim \mathcal{CN}(0, N_0 \mathbf{I})$ is the background noise vector. Let $\mathbf{P}_i = \mathrm{diag}(\mathbf{p}_i)$. Then, we have

$$\mathbf{x} = \underbrace{[(\mathbf{P}_1 \mathbf{F}) \ \dots (\mathbf{P}_D \mathbf{F})]}_{=\bar{\mathbf{P}}} \begin{bmatrix} \mathbf{e}_1 \\ \vdots \\ \mathbf{e}_D \end{bmatrix} + \mathbf{n}_\mathrm{p} = \bar{\mathbf{P}} \mathbf{e} + \mathbf{n}_\mathrm{p}, \tag{3}$$

where $\mathbf{e}_i = \sum_{k \in \mathcal{C}_i} \mathbf{h}_{i(k)}$ and $\mathbf{e} = [\mathbf{e}_1^{\mathrm{T}} \ \ldots \ \mathbf{e}_D^{\mathrm{T}}]^{\mathrm{T}}$. Here, $\mathcal{C}_i$ is the index set of the active devices that choose $\mathbf{p}_i$. Thus, $|\cup_{i=1}^{D} \mathcal{C}_i| = M$ and $\mathcal{C}_i \cap \mathcal{C}_m = \emptyset$ for $i \neq m$.

Since the number of active devices is M, there might be at most MP non-zero elements in $\mathbf{e}$. Note that $\mathbf{e}$ is a $DP \times 1$ vector, while the size of $\bar{\mathbf{P}}$ in (3) is $L \times DP$. From this, the estimate of $\mathbf{e}$ can be found as

$$\hat{\mathbf{e}} = \underset{\mathbf{e} \in \Sigma_{MP}}{\operatorname{argmin}} ||\bar{\mathbf{P}}\mathbf{e} - \mathbf{x}||^2. \quad (4)$$

This minimization is computational infeasible when L and D are large. However, since $\mathbf{e}$ can be seen as a sparse signal when $M \ll D$, we could use CS-based sparse signal estimation approaches to estimate $\mathbf{e}$.

The estimate of $\mathbf{e}$ from (3) can only provide the CSI of active devices. This CSI will be used to identify active devices in the second stage. We assume that the AP can detect M used pilot spreading sequences in the first stage (thus, there are at least M active devices). For convenience, the M estimated channel matrices are denoted by $\bar{\mathbf{H}}_m$, $m = 0, \ldots, M-1$. Once $\{\bar{\mathbf{H}}_m\}$ is available, in the second stage, the AP could identify the active devices and their data symbols.

B. Stage II: Device Identification and Signal Detection

As illustrated in Fig. 1, after Stage I, the AP can broadcast the pilot IDs that are not collided. Thus, in Stage II, we assume that the active devices that do not have any pilot collisions can transmit their signals with unique identification sequences.

For unique identification sequences, we can rewrite (1) as

$$\begin{bmatrix} \Re(\mathbf{r}) \\ \Im(\mathbf{r}) \end{bmatrix} = \sum_{k \in \mathcal{A}} \tilde{\mathbf{H}}_k \tilde{\mathbf{a}}_k + \begin{bmatrix} \Re(\mathbf{n}) \\ \Im(\mathbf{n}) \end{bmatrix}, \quad (5)$$

where $\tilde{\mathbf{H}}_k = \begin{bmatrix} \Re(\mathbf{H}_k) & -\Im(\mathbf{H}_k) \\ \Im(\mathbf{H}_k) & \Re(\mathbf{H}_k) \end{bmatrix}$ and $\tilde{\mathbf{a}}_k = \begin{bmatrix} \Re(\mathbf{a}_k) \\ \Im(\mathbf{a}_k) \end{bmatrix}$. For convenience, we denote by $\tilde{\mathbf{x}}$ the real-valued version of a complex-valued vector $\mathbf{x}$ throughout the paper. Since $d_k \in \{-1, +1\}$ is real-valued, we have

$$\tilde{\mathbf{a}}_k = \tilde{\mathbf{c}}_k d_k,$$

where $\tilde{\mathbf{c}}_k = \begin{bmatrix} \Re(\mathbf{c}_k) \\ \Im(\mathbf{c}_k) \end{bmatrix}$. Throughout the paper, we assume that $\tilde{\mathbf{c}}_k$ is Q-sparse. In this case, N_I becomes $N_I = \binom{2L}{Q}$. The resulting approach is referred to as the SIMA based approach.

For example, if $L = 64$ and $Q = 5$, we have $N_I \approx 7.6 \times 10^6$. Thus, the SIMA based approach using sparse $\mathbf{c}_k$ can generate a sufficiently large number of identification sequences for devices, although N_I is much smaller than that in the CDMA based approach, which is $2^{L-1} \approx 9 \times 10^{18}$ when $L = 64$.

Let $\mathbf{W}$ denote the complex-valued precoding matrix of size $L \times L$. We assume that this precoding matrix, $\mathbf{W}$, is used by all devices to mitigate frequency-selective fading as mentioned earlier. Throughout the paper, we assume that $\mathbf{W}$ is a unitary matrix of non-zero elements. Let $\tilde{\mathbf{W}} = \begin{bmatrix} \Re(\mathbf{W}) & -\Im(\mathbf{W}) \\ \Im(\mathbf{W}) & \Re(\mathbf{W}) \end{bmatrix} = [\tilde{\mathbf{w}}_1 \ \ldots \ \tilde{\mathbf{w}}_{2L}]$ and $\tilde{\mathbf{c}}_k$ be

$$\tilde{\mathbf{c}}_k = \sum_{i \in I_k} \tilde{\mathbf{w}}_i = \tilde{\mathbf{W}} \tilde{\mathbf{u}}_k, \ k = 0, \ldots, K-1, \quad (6)$$

where I_k is the unique index set for device k, which is used for the device identification, and $\tilde{\mathbf{u}}_k$ of size $2L \times 1$ is

$$[\tilde{\mathbf{u}}_k]_i = \begin{cases} \frac{1}{\sqrt{Q}}, & \text{if } i \in I_k; \\ 0, & \text{otherwise.} \end{cases} \quad (7)$$

For SIMA, we assume that $|I_k| = Q$. Note that $||\tilde{\mathbf{u}}_k|| = 1$ for normalization purposes. In (6), $\tilde{\mathbf{c}}_k$ is not sparse, but $\tilde{\mathbf{u}}_k$, which is Q-sparse. For convenience, $\tilde{\mathbf{u}}_k$ is referred to as the sparse identification vector (SIV) for device k, which is used in random access to allow device identification. For convenience, denote by $\tilde{\mathcal{U}}$ the set of the Q-sparse SIVs of size $2L \times 1$ that are defined as in (7). Note that $\mathbf{c}_k = \mathbf{W}\mathbf{u}_k$ if we define $\mathbf{u}_k$ as $\mathbf{u}_k = \tilde{\mathbf{u}}_{1:L} + j\tilde{\mathbf{u}}_{L+1:2L}$. For convenience, let

$$\mathcal{U} = \{\mathbf{u} \,|\, \mathbf{u} = \tilde{\mathbf{u}}_{1:L} + j\tilde{\mathbf{u}}_{L+1:2L}, \ \tilde{\mathbf{u}} \in \tilde{\mathcal{U}}\}. \quad (8)$$

Then, $\mathbf{u}_k \in \mathcal{U}$, while $\tilde{\mathbf{u}}_k \in \tilde{\mathcal{U}}$.

Denote by $\mathbf{v}_m \in \mathcal{U}$ the SIV used by the active device associated with the channel matrix $\bar{\mathbf{H}}_m$ that is estimated in Stage I. For convenience, denote by $\tilde{\mathbf{v}}_m \in \tilde{\mathcal{U}}$ the real-valued version of $\mathbf{v}_m$. Note that $\mathbf{u}_k \in \mathcal{U}$ is the unique SIV for device k, while $\mathbf{v}_m \in \mathcal{U}$ is the SIV of the active device that is associated with $\bar{\mathbf{H}}_m$ in Stage I. In Stage II, with known $\bar{\mathbf{H}}_m$, the AP can perform coherent detection to decide $\mathbf{v}_m$ as will be shown below. Once $\mathbf{v}_m$ is known, the AP can identify the active device associated with $\bar{\mathbf{H}}_m$ by finding the index $k(m)$ such that $\mathbf{u}_{k(m)} = \mathbf{v}_m$.

Consider $\mathbf{r}_t$, $t \in \mathcal{T}_{\mathrm{d}}$ in Stage II. For convenience, we omit the time index t. Then, we have

$$\begin{aligned} \mathbf{r} &= \sum_{k \in \mathcal{A}} \mathbf{H}_k \mathbf{a}_k + \mathbf{n} \\ &= [(\bar{\mathbf{H}}_0 \mathbf{W}) \ \ldots \ (\bar{\mathbf{H}}_{M-1} \mathbf{W})] \begin{bmatrix} \mathbf{v}_0 \bar{d}_0 \\ \vdots \\ \mathbf{v}_{M-1} \bar{d}_{M-1} \end{bmatrix} + \mathbf{n}, \end{aligned} \quad (9)$$

where $\bar{d}_m \in \mathcal{D}$ represents the data symbol that is transmitted by the active device associated with the channel matrix $\bar{\mathbf{H}}_m$. Letting $\mathbf{G}_m = \begin{bmatrix} \Re(\bar{\mathbf{H}}_m \mathbf{W}) & -\Im(\bar{\mathbf{H}}_m \mathbf{W}) \\ \Im(\bar{\mathbf{H}}_m \mathbf{W}) & \Re(\bar{\mathbf{H}}_m \mathbf{W}) \end{bmatrix}$, it can be shown that

$$\mathsf{r} = \begin{bmatrix} \Re(\mathbf{r}) \\ \Im(\mathbf{r}) \end{bmatrix} = \mathbf{G}\mathbf{b} + \tilde{\mathbf{n}}, \quad (10)$$

where $\tilde{\mathbf{n}} = \begin{bmatrix} \Re(\mathbf{n}) \\ \Im(\mathbf{n}) \end{bmatrix}$, $\mathbf{G} = [\mathbf{G}_0 \ \ldots \ \mathbf{G}_{M-1}]$ is the second-stage measurement matrix of size $2L \times 2LM$, and

$$\mathbf{b} = [(\tilde{\mathbf{v}}_0 \bar{d}_0)^{\mathrm{T}} \ \ldots \ (\tilde{\mathbf{v}}_{M-1} \bar{d}_{M-1})^{\mathrm{T}}]^{\mathrm{T}}.$$

Note that since $\tilde{\mathbf{v}}_m \in \tilde{\mathcal{U}}$ is a Q-sparse signal, $\bar{\mathbf{b}}$ of size $2LM \times 1$ in (10) is an MQ-sparse vector. Since the measurement matrix, $\mathbf{G}$, in (10) is available at the AP from Stage I, an estimate of $\mathbf{b}$ can be found as

$$\hat{\mathbf{b}} = \underset{\mathbf{b} \in \Sigma_{MQ}}{\operatorname{argmin}} ||\mathsf{r} - \mathbf{G}\mathbf{b}||^2. \quad (11)$$

Once $\mathbf{b}$ is estimated, the data symbols, $\bar{d}_m$'s, and the SIVs, $\tilde{\mathbf{v}}_m$'s, can be found from $\hat{\mathbf{b}}$. This shows that the identification of active devices can be carried out by estimating the sparse vector $\mathbf{b}$ in (11) using a low-complexity CS estimation method such as the orthogonal matching pursuit (OMP) algorithm.

IV. EM Algorithm for Joint Identification and Detection

In this section, we derive an EM algorithm for the joint active device identification and data detection with multiple symbols (note that the approach in Subsection III-B is valid for single symbol, i.e., $T = 1$).

Let $\mathcal{T}_{\rm d} = \{0, \ldots, T-1\}$, i.e., the number of data symbols in Stage II is T. Then, from (10), the received signal at the tth symbol transmission in Stage II is given by

$$\mathbf{r}_t = \mathbf{G}\mathbf{B}_t\mathbf{z} + \tilde{\mathbf{n}}_t,\ t = 0, \ldots, T-1, \tag{12}$$

where $\mathbf{B}_t = \mathrm{diag}(\bar{d}_{0,t} \ \ldots \ \bar{d}_{M-1,t}) \otimes \mathbf{I}$ and $\mathbf{z} = [\tilde{\mathbf{v}}_0^{\rm T} \ \ldots \ \tilde{\mathbf{v}}_{M-1}^{\rm T}]^{\rm T}$. Here, $\bar{d}_{m,t}$ is the tth data symbol transmitted by the active device associated with the channel matrix $\bar{\mathbf{H}}_m$ and $\tilde{\mathbf{n}}_t \sim \mathcal{N}\left(0, \frac{N_0}{2}\mathbf{I}\right)$ is an independent background noise. It is noteworthy that since each device has a unique identification sequence, $\tilde{\mathbf{v}}_m$ is invariant during T-symbol in (12).

With all received signal vectors, under the ML criterion, we have the following joint identification and detection problem:

$$\{\hat{\mathbf{z}}, \hat{\mathbf{B}}\} = \underset{\mathbf{z},\mathbf{B}}{\mathrm{argmax}} \prod_{t=0}^{T-1} f(\mathbf{r}_t|\mathbf{z}, \mathbf{B}_t) = \underset{\mathbf{z},\mathbf{B}}{\mathrm{argmin}} \sum_{t=0}^{T-1} ||\mathbf{r}_t - \mathbf{G}\mathbf{B}_t\mathbf{z}||^2, \tag{13}$$

where $f(\mathbf{r}_t|\mathbf{z}, \mathbf{B}_t)$ is the likelihood function for given $\mathbf{r}_t$ and $\mathbf{B} = [\mathbf{B}_0 \ \ldots \ \mathbf{B}_{T-1}]$, and proper constraints should be imposed on $\mathbf{z}$ and $\mathbf{B}$ (e.g., $\mathbf{z} \in \Sigma_{MQ}$). An exhaustive search to solve the problem in (13) is computationally infeasible. Thus, we may resort to the EM algorithm [11]. For the EM algorithm, we consider the ML approach to estimate $\mathbf{z}$ as follows:

$$\hat{\mathbf{z}} = \underset{\mathbf{z}\in\Sigma_{MQ}}{\mathrm{argmax}} \prod_{t=0}^{T-1} f(\mathbf{r}_t|\mathbf{z}), \tag{14}$$

where $f(\mathbf{r}_t|\mathbf{z})$ is the likelihood function of $\mathbf{z}$ for given $\mathbf{r}_t$. Taking $\mathbf{B}$ as the missing data (i.e., $\{\mathbf{r}_t, \mathbf{B}_t\}$ is considered the complete data, while $\{\mathbf{r}_t\}$ is the incomplete data), we can derive the EM algorithm, which is an iterative algorithm and consists of the E-step and M-step.

The E-step is given by

$$Q(\mathbf{z}\,|\,\hat{\mathbf{z}}^{(q)}) = \mathbb{E}_{\mathbf{B}}\left[\sum_{t=0}^{T-1} ||\mathbf{r}_t - \mathbf{G}\mathbf{B}_t\mathbf{z}||^2 \,\middle|\, \{\mathbf{r}_t\}, \hat{\mathbf{z}}^{(q)}\right], \tag{15}$$

where $\hat{\mathbf{z}}^{(q)}$ denotes the estimate of $\mathbf{z}$ at the qth iteration. Let

$$\begin{aligned} \mu_{m,t}^{(q)} &= \mathbb{E}[\bar{d}_{m,t}\,|\,\{\mathbf{r}_t\}, \hat{\mathbf{z}}^{(q)}] \\ \sigma_{m,t}^{(q)} &= \mathrm{Var}(\bar{d}_{m,t}\,|\,\{\mathbf{r}_t\}, \hat{\mathbf{z}}^{(q)}). \end{aligned} \tag{16}$$

Then, after some manipulations under the assumption that $\bar{d}_{m,t}$ is independent, it follows

$$Q(\mathbf{z}\,|\,\hat{\mathbf{z}}^{(q)}) = ||\mathbf{y} - \mathbf{A}^{(q)}\mathbf{z}||^2 + \mathbf{z}^{\rm H}\mathbf{\Delta}^{(q)}\mathbf{z}, \tag{17}$$

where

$$\mathbf{y} = [\mathbf{r}_0^{\rm T} \ \cdots \ \mathbf{r}_{T-1}^{\rm T}]^{\rm T}$$
$$\mathbf{A}^{(q)} = \begin{bmatrix} \mathbf{G}_0\mu_{0,0}^{(q)} & \cdots & \mathbf{G}_{M-1}\mu_{M-1,0}^{(q)} \\ \vdots & \ddots & \vdots \\ \mathbf{G}_0\mu_{0,T-1}^{(q)} & \cdots & \mathbf{G}_{M-1}\mu_{M-1,T-1}^{(q)} \end{bmatrix}$$
$$\mathbf{\Delta}^{(q)} = \begin{bmatrix} \mathbf{G}_0^{\rm H}\mathbf{G}_0\sigma_0^{(q)} & \cdots & \mathbf{0} \\ \vdots & \ddots & \vdots \\ \mathbf{0} & \cdots & \mathbf{G}_{M-1}^{\rm H}\mathbf{G}_{M-1}\sigma_{M-1}^{(q)} \end{bmatrix}.$$

The M-step is given by

$$\hat{\mathbf{z}}^{(q+1)} = \underset{\mathbf{z}\in\Sigma_{MQ}}{\mathrm{argmin}} ||\mathbf{y} - \mathbf{A}^{(q)}\mathbf{z}||^2 + \mathbf{z}^{\rm H}\mathbf{\Delta}^{(q)}\mathbf{z}. \tag{18}$$

Due to the sparsity constraint, i.e., $\mathbf{z} \in \Sigma_{MQ}$, it is not easy to perform the M-step to find $\hat{\mathbf{z}}^{(q+1)}$, although the cost function is quadratic in $\mathbf{z}$. We can resort to a low-complexity greedy algorithm to find an approximate solution to the problem in (18). Since

$$||\mathbf{y} - \mathbf{A}^{(q)}\mathbf{z}||^2 + \mathbf{z}^{\rm H}\mathbf{\Delta}^{(q)}\mathbf{z} = ||\mathbf{y}_{\rm ex} - \bar{\mathbf{A}}^{(q)}\mathbf{z}||^2, \tag{19}$$

where $\mathbf{y}_{\rm ex} = [\mathbf{y}^{\rm H} \ \mathbf{0}_{1\times L}]^{\rm H}$ and $\bar{\mathbf{A}}^{(q)} = \begin{bmatrix} \mathbf{A}^{(q)} \\ \mathbf{\Delta}^{(q)} \end{bmatrix}$, the M-step in (18) becomes

$$\hat{\mathbf{z}}^{(q+1)} = \underset{\mathbf{z}\in\Sigma_{MQ}}{\mathrm{argmin}} ||\mathbf{y}_{\rm ex} - \bar{\mathbf{A}}^{(q)}\mathbf{z}||^2. \tag{20}$$

The OMP algorithm can be used to find an approximate solution for $\mathbf{z}$ in (20), which is an $\bar{M}$-sparse signal, where $\bar{M} = MQ$. However, a better performance can be obtained if we take into account the structure of $\mathbf{z}$ as $\mathbf{z}$ is a concatenation of M Q-sparse signal blocks (i.e., the $\tilde{\mathbf{v}}_m$'s).

V. Simulation Results

In this section, we present simulation result for joint identification and detection using the EM algorithm derived in Subsection IV. We assume that the channel coefficients, $h_{k,i}$, are independent CSCG random variables with mean zero and variance $\frac{1}{P}$ (i.e., Rayleigh fading is assumed). For the precoding matrix $\mathbf{W}$, we consider a randomly generated complex-valued unitary matrix for each run.

With $T = 200$, we consider two types of CSI: perfect CSI and imperfect (or estimated) CSI. For imperfect CSI, we assume a fixed normalized mean squared error (NMSE) of the estimated CSI, which is set to 0.05 regardless of the SNR.

Fig. 2 shows the performance of the EM algorithm for the joint identification and detection in Stage II when $L = 64$, $M = 6$, $P = 3$, and $Q = 3$. We can see that the probability of unsuccessful identification decreases with the SNR and the performance can be improved through iterations as shown in Fig. 2 (a). This performance behavior is valid for both the cases of perfect and imperfect CSI. In Fig. 2 (b), the performance of signal detection for the case of correct identification is shown with bit error rate (BER). At a low SNR, the BER performances of perfect CSI and imperfect CSI

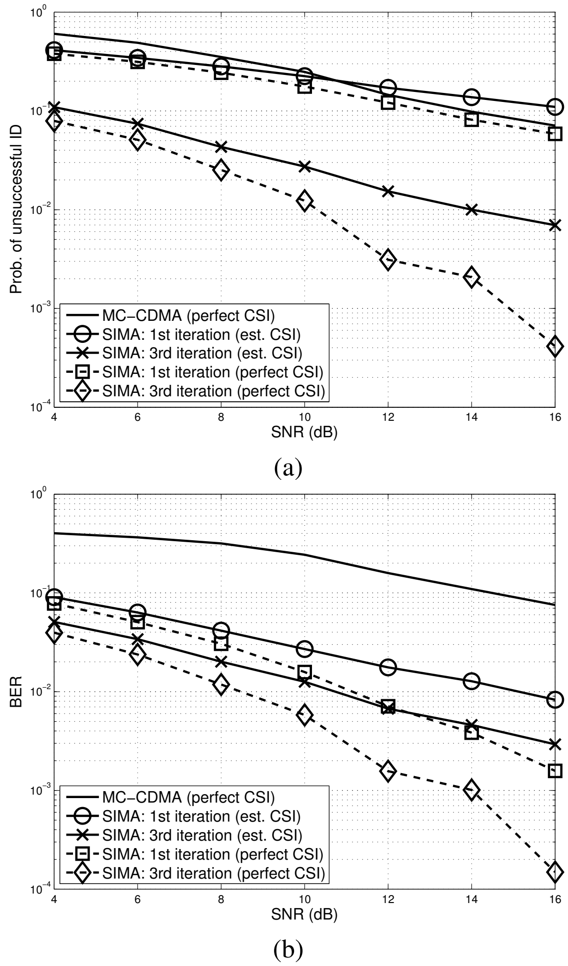

Fig. 2. Performances of the joint identification and detection in Stage II for various SNRs when $L = 64$, $M = 6$, $P = 3$, and $Q = 3$: (a) the probability of unsuccessful identification; (b) BER.

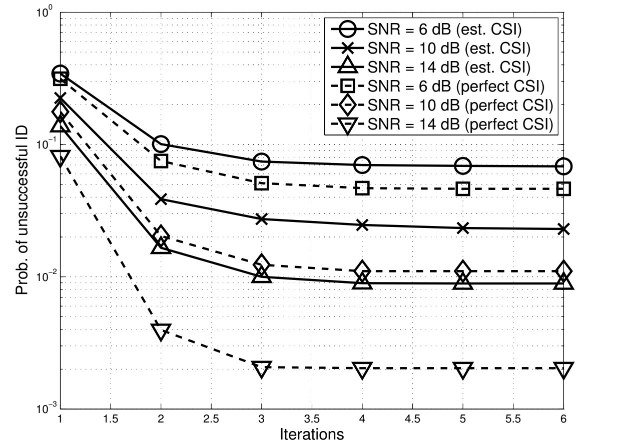

Fig. 3. Performance improvement of the EM algorithm over iterations in terms of the probability of unsuccessful identification when when $L = 64$, $M = 6$, $P = 3$, and $Q = 3$.

are not significantly different. However, as the SNR increases, the performance gap grows.

In order to see the impact of iterations in the EM algorithm, we show the probability of unsuccessful identification for various number of iterations in Fig. 3 when $L = 64$, $M = 6$, $P = 3$, $Q = 3$, and SNR $\in \{6, 10, 14\}$ dB. We can see that 3 iterations might be sufficient for reasonably high SNRs.

VI. Concluding Remarks

We introduced SIMA and applied it to uplink access in a wireless system of a large number of devices with low activity to exploit the sparsity of active devices as well as identification vectors for efficient identification of them. Since the device identification was carried out locally within the physical layer in the proposed multiple access scheme, it can simplify the architecture of wireless sensor networks to collect big data (as no central device identification is required). A two-stage scheme was proposed to receive signals from active devices with their identifications. We derived computationally efficient methods for the channel estimation of active devices in Stage I and for the joint identification and detection in Stage II using the EM algorithm. Simulation results have shown that the proposed two-stage transmission scheme can be effectively employed to the system of many devices for wireless IoT and the proposed methods can estimate CSI of active devices under reasonable conditions and identify them with SIVs well.

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