A Cross-Layer Approach to Data-aided Sensing using Compressive Random Access

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Abstract—In this paper, data-aided sensing as a cross-layer approach in Internet-of-Things (IoT) applications is studied, where multiple IoT nodes collect measurements and transmit them to an Access Point (AP). It is assumed that measurements have a sparse representation (due to spatial correlation) and the notion of Compressive Sensing (CS) can be exploited for efficient data collection. For data-aided sensing, a node selection criterion is proposed to efficiently reconstruct a target signal through iterations with a small number of measurements from selected nodes. Together with Compressive Random Access (CRA) to collect measurements from nodes, compressive transmission request is proposed to efficiently send a request signal to a group of selected nodes. Error analysis on compressive transmission request is carried out and the impact of errors on the performance of data-aided sensing is studied. Simulation results show that data-aided sensing allows to reconstruct the target information with a small number of active nodes and is robust to nodes’ decision errors on compressive transmission request.

Index Terms—Data-aided sensing; Internet-of-Things (IoT); Cross-Layer

I. INTRODUCTION

There have been extensive efforts to realize the idea of the Internet of Things (IoT) as the IoT has a huge impact on a number of applications ranging from environmental monitoring to factory automation to smart cities and fosters new business growth [1] [2] [3] [4]. By providing the connectivity for devices (e.g., sensors and actuators), a number of IoT applications can be emerged. For example, in [5], an IoT-based implementation for environmental condition monitoring in homes is studied.

To implement IoT systems, various reference architectures for IoT infrastructure are proposed [3]. In general, the bottom layer, called objects or perception layer, is to collect and process information or data from devices. This is often divided into two sub-layers, namely connectivity layer and data layer, which are responsible for collecting data and processing collected data, respectively, in an IoT system. The two layers are usually decoupled for ease of implementation as in [6], where an IoT platform is used as a Wireless Sensor Network (WSN) for environmental sensing and data delivering.

In this paper, however, a cross-layer design to combine data sensing and processing is considered to make data-aided sensing possible. Data-aided sensing is a novel approach that can actively choose IoT devices/sensors with desired information or measurements by analyzing existing data sets to improve the overall quality of data sets in iterations. For example, as shown in Fig. 1, the next sensing point or sensor can be decided by analyzing the existing data set for a better outcome provided that the system allows to choose sampling points or IoT devices/sensors at certain locations, while the first sampling point can be randomly decided. Through iterations in data-aided sensing, the outcome can be improved. As a result, the number of iterations with data-aided sensing can be smaller than that without data-aided sensing to reach a certain desired quality of data set.

Certainly, cross-layer design for data-aided sensing may not be suitable to every IoT systems. In general, for efficient data-aided sensing, certain features of connectivity layer are to be supported. It is expected that devices are able to directly connect to a Base Station (BS) or Access Point (AP), which requires long-range connectivity with star topology. A number of approaches are considered to support long-range connectivity such as Low-Power Wide Area Networking (LP-WAN) and Machine-Type Communication (MTC) [7] [8].

In MTC, in order to support a large number of devices with sparse activity, the notion of Compressive Sensing (CS) [9] [10] [11] has been adopted, which results in Compressive Random Access (CRA) [12] [13] [14] [15]. In CRA, multiple IoT devices/sensors with unique signature sequences can simultaneously transmit, and a receiver uses a CS-based Multi-User Detection (MUD) algorithm to detect their activity as well as their signals [16] [17]. In this paper, CRA is assumed for connectivity layer as it can also be used for active data collection by exploiting the assignment of a unique signature sequence to each device in data-aided sensing.

For data-aided sensing, in this paper, a specific application where the AP aims to reconstruct a target signal from as few devices’ measurements as possible is mainly considered under the assumption that the set of measurements has a sparse representation. In WSNs, when the measurements of sensors are spatially correlated, they can have a sparse representation and the notion of CS can be exploited for efficient data collection [18] [19] [20]. In this case, thanks to data-aided
sensing, measurements from only a fraction of devices may be needed for the AP to have a full picture (a reconstructed target signal), which may result in a high energy efficiency as well as a short reconstruction time.

The rest of the paper is organized as follows. In Section II, a signal model with a sparse representation is presented to study data-aided sensing. The reconstruction of a target signal from randomly collected measurements (based on the notion of CS) and CRA with multiple nodes are discussed in Section III. In Section IV, two different approaches to collect measurements are studied and the node selection criterion for data-aided sensing is proposed. To collect measurements from the nodes that are chosen according to the node selection criterion, a simple but efficient approach for controlled access is developed in Section V and its error analysis is presented in Section VI. Simulation results are shown in Section VII and the paper is concluded with remarks in Section VIII.

Notation: Matrices and vectors are denoted by upper- and lower-case boldface letters, respectively. The superscripts T and H denote the transpose and complex conjugate, respectively. The p-norm of a vector a is denoted by \( \|a\|_p \). (If \( p = 2 \), the norm is denoted by \( |a| \) without the subscript). The support of a vector is denoted by \( \text{supp}(x) \). \( E[\cdot] \) and \( \text{Var}(\cdot) \) denote the statistical expectation and variance, respectively. \( CN(a, \mathbf{R}) \) represents the distribution of Circularly Symmetric Complex Gaussian (CSCG) random vectors with mean vector \( a \) and covariance matrix \( \mathbf{R} \). The Q-function is given by \( Q(x) = \int_{x}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-t^2/2} dt \).

II. SIGNAL MODEL FOR IOT DATA COLLECTION

Suppose that a number of IoT nodes\(^1\) are deployed in a certain site or cell to collect and transmit measurements to an AP for IoT sensing (or data collection) in a certain application (e.g., for environmental monitoring). Denote by \( K \) the number of IoT nodes and by \( m_k \) the measurement at node \( k \in \mathcal{K} = \{1, \ldots, K\} \). The AP can collect measurements from the nodes and process them to create a target information for the site. For example, if each node sends the temperature at each location, the AP can build a heat map for the site.

In this paper, it is assumed that the signal vector obtained from all the nodes’ measurements has a sparse representation [21] [22] [20]. Let \( \mathcal{D} = \{m_k, k \in \mathcal{K}\} \). For the sake of simplicity, the target signal is assumed to be a \( K \times 1 \) vector, denoted by \( v \), as follows:

\[
[v]_k = m_k \in \mathbb{R}, \quad k \in \mathcal{K}.
\]

Furthermore, \( v \) can be represented by a sparse vector \( s \in \mathbb{R}^{M \times 1} \). To this end, it is assumed that

\[
v_k = \mathbf{b}_k^T s, \quad k \in \mathcal{K},
\]

where \( \mathbf{b}_k \in \mathbb{R}^{M \times 1} \) is the measurement vector at node \( k \), which is known at the AP.

From (1), \( v \) becomes \( v = \mathbf{B}^T s \), where \( \mathbf{B} = [\mathbf{b}_1 \ldots \mathbf{b}_K]^T \in \mathbb{R}^{M \times K} \). Throughout the paper, it is assumed that \( \|s\|_0 = S \), i.e., \( s \) is a \( S \)-sparse vector, where \( S \ll K \). As a result, it is possible to obtain \( v \) once \( s \) is known. In other words, it might be possible to estimate \( v \) without knowing all the nodes’ measurements.

For data-aided sensing, with multiple rounds of sensing, multiple access is employed to receive multiple measurements in each round as in Fig. 2. Let \( \mathcal{D}_0 \) denote the initial set of measurements associated with a subset of \( \mathcal{K} \), denoted by \( \mathcal{I}_0 \). For convenience, let \( |\mathcal{I}_0| = N \), where \( N \ll K \), and denote by \( \mathcal{I}_1 \) the index set of active nodes in round \( q \) throughout the paper. Since no data sets are available in round 0, \( \mathcal{I}_0 \) can be a random index set. Once \( \mathcal{D}_0 \) is available at the AP from random active nodes as in Fig. 2, the AP can determine the next index set of active nodes that can improve the quality of data set (i.e., the estimation accuracy of \( v \)), which is denoted by \( \mathcal{I}_1 \). Through iterations, the AP can have a (growing) data set that can effectively improve the estimate of \( v \).

III. RANDOM SENSING VIA COMPRESSIVE RANDOM ACCESS

Since \( S \ll K \), in order to find \( s \), it may not be necessary to ask all the nodes to transmit their measurements. That is, provided that the support of \( s \) is known, the AP only needs to have measurements from \( S \) nodes. In this case, the time to acquire \( v \) becomes shorter by a factor of \( K/S \). In addition, the life time of all IoT nodes increases. However, the support of \( s \) is unknown and more than \( S \) nodes need to transmit their measurements. According to [9] [10] [11], it might be still possible to keep the number of the nodes transmitting measurements small by exploiting the sparsity of \( s \) to reconstruct \( v \) based on the notion of CS. In this section, random sensing or projection via random access is studied for the initial sensing.

A. Random Sensing

Suppose that each node can decide whether or not it transmits its measurement randomly in the initial round, i.e., round 0. In this case, as shown in Fig. 2, a fraction of nodes become active (at a time) and transmit their measurements. Then, the AP can have a random subset of \( v \) and the resulting operation is referred to as random sensing in this paper.

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\(^1\)Throughout the paper, it is assumed that nodes, devices, and sensors are interchangeable.
Denote by $\mathcal{I} = \mathcal{I}_0$ the set of the active devices transmitting their signals, which is a random index set of $N (\leq K)$ active nodes because the AP does not know which nodes are active or not. To be precise, let

$$\mathcal{I} = \{i_1, \ldots, i_N\}, \ i_n \in \mathcal{K},$$ (2)

where $i_n$ represents the index of the $n$th active node (thus, the $i_n$'s are unique). The subvector of $\mathbf{v}$ associated with $\mathcal{I}$ is denoted by $\mathbf{w}$ and let $\Psi = [b_{i_1} \cdots b_{i_N}]^T$. Then, it can be shown that

$$\mathbf{w} = \Psi s \in \mathbb{R}^{N \times 1},$$ (3)

which can be seen as a random sensing or sampling of $\mathbf{v}$. It is known that if $N \geq CS \log \left( \frac{2^L}{\delta} \right)$, where $C$ is a constant, $\mathbf{s}$ can be recovered from $\mathbf{w}$ under certain conditions of $\Psi$ in (3) [9] [10] [11]. Once $\mathbf{s}$ is available, $\mathbf{v}$ can be obtained from (1). In other words, without collecting all the measurements from $K$ nodes, it is possible to estimate $\mathbf{v}$ from $N$ nodes' measurements (i.e., $\mathbf{w}$).

**B. Compressive Random Access**

For random sensing, each node can locally decide whether or not to transmit with a certain access probability, denoted by $p_a$, which results in random access. In this subsection, a random access method is discussed with a unique signature for each node so that the AP knows the node associated with each measurement when it recovers measurements from the received signal.

Suppose that each node has a unique signature sequence consisting $L$ elements, denoted by $c_k \in \mathbb{C}^{L \times 1}$. For normalization purposes, it is assumed that $||c_k||^2 = 1$ for all $k$. In addition, node $k$ transmits its signal to deliver the measurement $\mathbf{m}_k$ to the AP. Then, the received signal at the AP becomes

$$\mathbf{r}_t = \sum_{k \in \mathcal{I}} h_k \sqrt{P_k} c_k d_{k,t} + \mathbf{n}_t, \ t = 0, \ldots, T - 1,$$ (4)

where $\mathbf{n}_t \sim \mathcal{CN}(0, N_0 \mathbf{I})$ is the background noise sequence and $h_k$ represents the channel coefficient from node $k$ to the AP, and $P_k$ represents the transmit power. Here, $d_{k,t}$ represents the $t$th data symbol and $T$ denotes the length of packet. The resulting system can be seen as a code division multiple access [23] [24] system since $c_k$ is not only a signature sequence, but also a spreading sequence as shown in (4). Thus, it is possible for the AP to decode the signals when multiple nodes transmit their measurements simultaneously.

From (4), the received signal at the AP is re-written as

$$\mathbf{r}_t = \mathbf{C}\mathbf{x}_t + \mathbf{n}_t,$$ (5)

where $\mathbf{C} = [c_1 \ldots c_K], \ x_t = [x_{1,t} \ldots x_{K,t}],$ and $x_{k,t} = h_k \sqrt{P_k} a_k d_{k,t}$. Here, $a_k \in \{0, 1\}$ is the activity variable for node $k$. Throughout the paper, Time Division Duplexing (TDD) is assumed so that the channel reciprocity holds. Thus, when the AP transmits a beacon signal, it can also be used as a pilot signal that allows each node to estimate $h_k$. With known channel gain, the transmit power at node $k$ can be decided as

$$P_k = \frac{P_{rx}}{|h_k|^2},$$ (6)

where $P_{rx}$ is the required received signal power at the AP. In (5), $\mathcal{I} = \text{supp}(\mathbf{a})$, where $\mathbf{a} = [a_1 \ldots a_K]^T$. Since the transmit power at each node is limited, if $P_k > P_{max}$ or

$$|h_k|^2 < \frac{P_{rx}}{P_{max}} = \omega,$$ (7)

where $P_{max}$ is the maximum transmit power, node $k$ cannot transmit its measurement. In this case, it is assumed that $a_k$ becomes 0 (as node $k$ is not active) and the resulting power control policy becomes the truncated channel inversion power control policy [25].

Since $h_k$ is random and some nodes may not be active when in sleep mode, $a_k$ becomes an independent Bernoulli random variable. Thus, in this paper, it is assumed that $\text{Pr}(a_k = 1) = p_a$ and $\text{Pr}(a_k = 0) = 1 - p_a$, where $p_a \in (0, 1)$ denotes the access probability. Consequently, with the power control in (6), $x_{k,t} = \sqrt{P_{rx}} d_{k,t} a_k$, where $a_k \sim \text{B}(1, p_a)$. Here, $\text{B}(n, p)$ represents the binomial distribution with parameters $n$ and $p$.

Note that since a high channel gain is a necessary condition for a node to be active, it is expected that

$$p_a \leq \text{Pr}(|h_k|^2 \geq \omega).$$

At the AP, CS-based MUD can not only recover the signals from active nodes, but also identify the active nodes (by estimating $\mathcal{I}$). The resulting random access is referred to as CRA [12] [14] [26]. In data-aided sensing, after the initial round, certain nodes will be asked to transmit their measurements by the AP. In this case, coordinated transmission or controlled access will be used. However, CRA is still required due to errors that occur when a request signal is sent to nodes, which will be explained in Section VI.

**IV. A CROSS-LAYER DESIGN FOR DATA- AIDED SENSING**

In the initial round, the number of active devices, $N$, may not be sufficiently large$^2$ for the AP to have a good estimate of $\mathbf{v}$. In this case, another round of sensing/transmissions via CRA is required, which may result in a different random sensing of $\mathbf{v}$. In this section, repeated random sensing is considered with multiple rounds till a successful recovery of $\mathbf{v}$, and data-aided sensing is proposed, which would require a smaller number of measurements than simple repeated random sensing by actively choosing nodes for a better reconstruction.

**A. Repeated Random Sensing**

Suppose that each node decides to be active or not based on its channel gain in each round (due to fading, the channel coefficient is assumed to be independent in each round). In this case, random active nodes in each round are to transmit their measurements via CRA, and the AP can acquire the measurements from them and form $\mathcal{D}_q$ in each round $q$ to estimate $\mathbf{v}$ together with their associated measurement vectors, where

$$\mathcal{D}_q = \{m_k, \ k \in \mathcal{K}_q\},$$ (8)

$^2$Since the sparsity of $\mathbf{s}$, $S$, is unknown, the number of active nodes, $N$, cannot be determined in advance to guarantee a successful recovery with one round.
which is a subset of \( D \). Here, \( K_q = \cup_{i=0}^{q} I_i \). As \( q \) increases (under the assumption that the nodes transmitted before do not transmit again), more measurements are available at the AP (i.e., \( D_q \) increases), which can lead to a better recovery performance. To see this clearly, let \( w_q \) and \( B_q \) be the subvector of \( v \) and the submatrix of \( B \) corresponding to \( I_q \), respectively. Each round can be seen as another random projection of \( s \), and in round \( q \), the AP can have

\[
\begin{bmatrix}
w_0 \\
\vdots \\
w_q
\end{bmatrix} = [B_0 \ldots B_q]^T s.
\]  

(9)

Let \( N_q = |I_q| \). While the sparsity of \( s \) is fixed, the accumulated number of measurements, i.e., \( N_0 + \ldots + N_q \), increases with \( q \). Thus, it is expected that the AP is able to reconstruct \( v \) by finding \( s \) in (9) with a sufficiently large number of rounds in repeated random sensing.

However, since the time it takes to complete the reconstruction as well as the total energy consumption at devices (to sense and transmit their measurements) increase with the number of rounds, it is desirable to have a small number of rounds if possible.

**B. Data-aided Sensing**

In this subsection, a method is studied for data-aided sensing that chooses a set of new measurements for a better reconstruction based on the existing measurements obtained from the previous rounds of sensing.

In data-aided sensing, the index set of the active nodes in round \( q \) is decided by the data set up to round \( q - 1 \). That is, \( I_q \) is given by

\[
I_q = G_q(D_{q-1}),
\]

(10)

where \( G_q(\cdot) \) is a certain function generating an index set of the active nodes that potentially have better measurements for the reconstruction (among the inactive nodes up to round \( q - 1 \)) based on the data set \( D_{q-1} \). Note that in repeated random sensing, \( I_q \) is decided by nodes, which means that \( G_q(\cdot) \) is independent of \( D_{q-1} \).

For convenience, \( K_q = K \setminus K_{q-1} \), which is the complement set of \( K_{q-1} \). Let \( \hat{s}_q \) denote the estimate of \( s \) after round \( q \). In addition, let \( \hat{v}_q = B^T \hat{s}_q \)

(11)

be the estimate of \( v \) after round \( q \). The AP may want a careful selection of active nodes for the next round to improve recovery performance rather than a random selection. Let \( v_q(K_{q-1} \cup I_q) \) denote the estimate of \( v_q \) with data set associated with \( K_{q-1} \cup I_q \). Then, for example, the best index set in round \( q \) to minimize the squared norm of the error vector can be found as

\[
\hat{I}_q = \arg\min_{I_q \subseteq K_{q-1} \cup I_q, |I_q| = N} ||v - v_q(K_{q-1} \cup I_q)||^2,
\]

(12)

which is unfortunately impossible to implement as \( v \) is not available at the AP. To avoid this, the Mean Squared Error (MSE) can be employed as a performance criterion provided that the statistical properties of \( v \) is available. In this paper, however, a different approach that can be employed without knowing statistical properties of \( v \) is proposed.

Consider the following set:

\[
I_q = \{k_{q,1}, \ldots, k_{q,N_q}\},
\]

where \( k_{q,i} \) is the index of the node that has the \( i \)th largest measurement among \( K \setminus K_{q-1} \), i.e.,

\[
k_{q,i} = \arg\max_{k \in K_{q-1}} |v_k|^2, \quad q \geq 1,
\]

(13)

where \( K_{q-1} \) is the complement set of

\[
K_{q,i} = K_{q-1} \cup \{k_{q,1}, \ldots, k_{q,i-1}\}.
\]

(14)

In (13), \( v \) is required to choose the next index set. Since \( v \) is not available, \( v \) can be replaced with its estimate in the previous round, i.e., \( \hat{v}_{q-1} \). In this case, it can be shown that

\[
k_{q,i} = \arg\max_{k \in K_{q,i}} |\hat{v}_{q-1,k}|^2
\]

\[
= \arg\max_{k \in K_{q,i}} |b_k^T \hat{s}_{q-1}|^2, \quad q \geq 1,
\]

(15)

which becomes a node selection criterion for data-aided sensing that depends on the previous estimate \( \hat{v}_{q-1} \).

Suppose that the correlation of \( b_k \) and \( b_{k'} \) is high, where \( k \neq k' \). In this case, it is expected that \( v_k \) and \( v_{k'} \) can be highly correlated. Thus, although the measurement of node \( k \) has a large magnitude, it may not help improve the performance if \( v_{k'} \) is already available at the AP. This can be taken into account and the resulting node selection criterion for data-aided sensing becomes

\[
k_{q,i} = \arg\max_{k \in K_{q,i}} \min_{i \in K_{q,i}} |b_k^T b_{i}|^2, \quad q \geq 1.
\]

(16)

In (16), \( I_q \) for round \( q \) can be clearly determined from \( \hat{s}_{q-1} \), which is obtained from \( D_{q-1} \), for data-aided sensing.

In data-aided sensing, since the AP chooses active nodes using the node selection criterion in (16), there should be interactions between connectivity and data layers in an IoT system, and controlled access is required to acquire measurements from the selected nodes. As a result, as opposed to repeated random sensing (where there is no interaction between connectivity and data layers), data-aided sensing becomes a cross-layer approach.

**V. CONTROLLED ACCESS FOR DATA-AIDED SENSING**

In this section, an efficient controlled access scheme with low signaling overhead is discussed for data-aided sensing by exploiting unique signature sequences of nodes.

**A. Compressive Transmission Request**

For controlled access, certain request signals are to be sent to nodes from the AP in data-aided sensing, which are not necessary in repeated random sensing. Thus, if the length of request signals is long, it may offset the advantage of data-aided sensing over repeated random sensing. To avoid it, a simple but efficient approach is developed using the structure of CRA considered in Subsection III-B.
Prior to round $q$, the AP can request the nodes selected by (15) to transmit their measurements, i.e., it can send a request message to each node in $\mathcal{I}_q$ at a time. However, the total time to request becomes proportional to $|\mathcal{I}_q|$. To shorten the time to request, the broadcast nature of the wireless medium and the structure of CRA can be exploited so that one request signal might be sufficient. To this end, the following downlink probe or request signal can be transmitted from the AP to the nodes:

$$p_q = \sum_{k \in \mathcal{I}_q} c_k. \hspace{1cm} (17)$$

For simplicity, it is assumed that $N_q = |\mathcal{I}_q| = N$ for all $q$ in the rest of this paper. The channel coefficient from the AP to node $k$ becomes $h_k$ based on the channel reciprocity in TDD and the received (compressive transmission) request signal becomes

$$y_k = h_k \frac{A_{ap}}{|p_q|} p_q + n_k, \hspace{1cm} (18)$$

where $n_k \sim \mathcal{CN}(0, N_0 I)$ is the background noise vector at node $k$ and $A_{ap}$ is the amplitude of the request signal from the AP. The resulting request signal is referred to as compressive transmission request signal.

**B. Hypothesis Testing for Request Signal Detection**

Since nodes are requested by the AP to transmit their measurements from round 1 in data-aided sensing, each node (not yet transmitted) needs to perform hypothesis testing with the received request signal, $y_k$, to see whether or not it is requested. In this subsection, hypothesis testing is studied using the Log-Likelihood Ratio (LLR) [27] and find the error probabilities.

At node $k$, in order to see whether or not it is requested to transmit its measurement, it can use the following output of the correlator with its signature sequence as a test statistic:

$$z_k = \Re \left( (h_k c_k) \bar{y}_k \right) = |h_k|^2 \frac{A_{ap}}{|p_q|} \mathbb{I}(k \in \mathcal{I}_q) + \Re (h_k w_k), \hspace{1cm} (19)$$

where $\mathbb{I}(\cdot)$ represents the indicator function and $w_k$ is the interference-plus-noise vector. Suppose that each element of $c_k$ is random and is one of $\{ (\pm 1 \pm j)/\sqrt{2L} \}$. Then, $c_k^H c_i, i \neq k$, can be approximated as a Gaussian random variable (thanks to the central limit theorem) with zero mean and variance $\frac{1}{L}$. In addition, it is assumed that $|\bar{p}_q|^2 \approx N$ by approximating $c_k^H c_i \approx 0$ for $k \neq i$ (which might be reasonable when $L$ is sufficiently large). Let $H_1$ and $H_0$ denote the hypotheses of $k \in \mathcal{I}_q$ and $k \notin \mathcal{I}_q$, respectively. Then, the Probability Density Function (pdf) of $z_k$ under hypothesis $p$, denoted by $f_p(z_k), p \in \{0, 1\}$, is approximately given by

$$f_0(z_k) = \mathcal{N} \left( 0, \frac{|h_k|^2 \sigma_{w,0}^2}{2} \right) \hspace{1cm} (20)$$

$$f_1(z_k) = \mathcal{N} \left( \sqrt{P_{ap}} |h_k|^2, \frac{|h_k|^2 \sigma_{w,1}^2}{2} \right),$$

where $P_{ap} = \frac{A_{ap}^2}{N}$ and

$$\sigma_{w,1}^2 = E[|w_k|^2] = E \left[ |c_k^H \left( \sum_{i \in \mathcal{I}_q} c_i + n_k \right) |^2 \right]$$

$$= P_{ap} \frac{N - 1}{L} + N_0$$

$$\sigma_{w,0}^2 = P_{ap} \frac{N}{L} + N_0. \hspace{1cm} (21)$$

A device that did not transmit yet will have a higher probability to be requested as the number of rounds increases, and the a priori probabilities in round $q$ becomes $P_q(H_0) = \frac{K - qN}{K (q - 1) N}$ and $P_q(H_1) = \frac{N}{K (q - 1) N}$. Here, $K - (q - 1)N$ is the number of the devices that did not transmit their measurements until round $q$.

If node $k$ does not transmit its measurement up to round $q - 1$, in round $q$, it can consider the following LLR test:

$$U_k = \ln \frac{f_1(z_k)}{f_0(z_k)} > \tau_q, \hspace{1cm} (22)$$

where $\tau_q$ is a threshold. Letting $\tau_q = \ln \frac{P_{ap}(H_0)}{P_{ap}(H_1)} = \ln \frac{K - qN}{N}$, the resulting test is based on the Maximum A Posteriori Probability (MAP) criterion. When $L$ is sufficiently large, i.e., $\frac{1}{L} \ll 1$, it can be shown that $\sigma_{w,0}^2 \approx \sigma_{w,1}^2$ and the test in (22) can be approximated as follows:

$$z_k > \sqrt{\frac{P_{ap}}{2}} |h_k|^2 + \frac{\sigma_{w,0}^2 \tau_q}{2 \sqrt{P_{ap}}}. \hspace{1cm} (23)$$

Let $\gamma = \frac{P_{ap}}{\sigma_{w,0}^2}$, which is the downlink signal-to-interference-plus-noise ratio (SINR). If $\tau_q = |h_k|^2 \gamma u_q$, it can be shown that

$$z_k > \sqrt{\frac{P_{ap}}{2}} |h_k|^2 (1 + u_q \gamma). \hspace{1cm} (24)$$

Here, the design parameter, $\gamma u_q$, which is referred to as the scaled decision parameter for convenience, will be discussed in Section VI. Note that since the truncated channel inversion power control policy is considered in this paper, as in (7), if the channel gain is weak, the node cannot respond to the request although it can correctly detect the request signal.

A reliable approach can be adopted to deliver the request signal to nodes. For example, a Hybrid Automatic Repeat reQuest (HARQ) protocol [28] can be used to deliver a request signal through a dedicated downlink channel. In this case, the signaling overhead becomes high although the request signal can be reliably delivered (with a very low error probability). On the other hand, the compressive transmission request approach (which is aimed at low signaling overhead) in this section is not sufficiently reliable and results in erroneous decision at a node with a relatively high probability. However, even if a node that is not requested sends its measurement, the AP can still utilize this information. Thus, erroneous decisions on the request signal at nodes may have little effect on the overall performance of data-aided sensing, which justifies using compressive transmission request with low signaling overhead.
VI. Error Analysis

In this section, possible erroneous decisions at a node are studied when the compressive transmission request is used and their impact on the performance.

A. Decision Errors in Downlink

In round \( q \) (\( q \geq 1 \)) (i.e., after the initial round), a certain node can be requested to transmit its measurement in data-aided sensing. However, the node may not correctly detect this request signal or the required transmit power can be higher than \( P_{\text{max}} \) due to fading, which makes the node unable to respond in round \( q \). This results in a Missed Detection (MD) event in downlink. The probability of MD for \( k \in I_q \) becomes

\[
P_{\text{MD},q} = \Pr(U_k < \tau_q, |h_k|^2 \geq \omega | k \in I_q) \\
+ \Pr(|h_k|^2 < \omega | k \in I_q).
\] (25)

Furthermore, node \( k \notin I_q \) happens to miss its transmission although it is not asked with the following probability:

\[
P_{\text{FA},q} = \Pr(U_k \geq \tau_q, |h_k|^2 \geq \omega | \not k \in I_q),
\] (26)

which is the probability of False Alarm (FA). Due to the events of MD and FA, which are referred to as downlink (decision) errors for convenience, the index set of active nodes in round \( q \) can be different from \( I_q \). Thus, it is necessary for the AP to perform CS-based MUD as in round 0 to not only decode the signals, but also identify active nodes.

When \( L \) is sufficiently large, (24) can be used to round the probability of FA. From the pdf of \( z_k \) under \( H_0 \) in (20), it can be shown that

\[
\Pr\left(z_k \geq \frac{\sqrt{P_{\text{ap}}}|h_k|^2}{2}(1 + u_q \gamma) | H_0, h_k\right)
= \int_{\sqrt{P_{\text{ap}}}|h_k|(1 + u_q \gamma)/2}^{\infty} \frac{1}{\sqrt{\pi|h_k|^2 \sigma_w^2}} e^{-\frac{|h_k|^2 z_k^2}{2 \sigma_w^2}} \, dz_k
= Q\left(\frac{|h_k|}{\sqrt{2}} \sqrt{(1 + u_q \gamma)}\right).
\] (27)

Note that for a Rayleigh channel, \( |h_k|^2 \) has the following exponential pdf:

\[
G = |h_k|^2 \sim f_G(g) = \exp(-g), \quad g \geq 0,
\] (28)

under the assumption that the channel power gain is normalized, i.e., \( \mathbb{E}[|h_k|^2] = 1 \). Then, the average probability of FA can be approximately obtained as

\[
P_{\text{FA},q} \approx \int_{0}^{\infty} Q\left(\frac{g}{2} \sqrt{(1 + u_q \gamma)}\right) f_G(g) \, dg
\approx \int_{0}^{\infty} \frac{e^{-\frac{g(1 + u_q \gamma)^2}{4}} + e^{-\frac{g(1 + u_q \gamma)^2}{3}}}{12} \, dg
= \frac{e^{-\omega(1 + \frac{2}{3}(1 + u_q \gamma)^2)}}{12(1 + \frac{2}{3}(1 + u_q \gamma)^2)} + \frac{e^{-\omega(1 + \frac{2}{3}(1 + u_q \gamma)^2)}}{4(1 + \frac{2}{3}(1 + u_q \gamma)^2)}\] (29)

Similarly, after some manipulations, it can be shown that

\[
P_{\text{MD},q} \approx \int_{\omega}^{\infty} Q\left(\frac{\sqrt{g}}{2} \sqrt{(1 - u_q \gamma)}\right) f_G(g) \, dg
+ \int_{0}^{\omega} f_G(g) \, dg
\approx \frac{e^{-\omega(1 + \frac{2}{3}(1 - u_q \gamma)^2)}}{12(1 + \frac{2}{3}(1 - u_q \gamma)^2)} + \frac{1 - e^{-\omega}}{4(1 + \frac{2}{3}(1 - u_q \gamma)^2)}.
\] (30)

In addition, as shown in (25), the probability of MD is lower-bounded by \( \Pr(|h_k|^2 < \omega | k \in I_q) = \Pr(|h_k|^2 < \omega) = 1 - e^{-\omega} \), which is independent of \( \gamma \). Thus, although \( \gamma \to \infty \), the average probability of MD cannot be low, while the average probability of FA approaches 0.

Note that from (29) and (30), it can be shown that the probability of MD increases and that of FA decreases with \( \gamma u_q \). In addition, to keep both the error probabilities reasonably low, it is required that \( 1 + u_q \gamma > 0 \) and \( 1 - u_q \gamma > 0 \), or

\[-1 < u_q \gamma < 1,\] (31)

i.e., the scaled decision parameter, \( u_q \gamma \), has to be bounded between \(-1 \) and \( 1 \).

B. CRA and Design Issues

According to (30) and (29), there might be downlink errors (i.e., MD and FA events) and the AP expects to see that the actual index set of active nodes, which is denoted by \( \hat{I}_q \), in round \( q \geq 1 \) may differ from \( I_q \). From this, even in data-aided sensing, CRA plays a key role in receiving measurements from active nodes, because the AP still needs to perform the activity detection to estimate \( \hat{I}_q \).

The performance of CRA is studied in [14] based on the notion of multiple measurement vectors (MMV) [30] [31]. As in (4), for a sufficiently long length of packet, the notion of MMV can be applied to the activity detection at the AP. Under certain conditions, it is possible to detect up to \( L - 1 \) signals [30] [31]. In practice, however, the number of the signals that can be detected is smaller than \( L - 1 \) due to the background noise as well as the limited complexity of the receiver algorithm used. For convenience, let \( \bar{N} \) be the maximum number of the signals that can be detected at the AP with a high probability, where \( \bar{N} \leq L - 1 \). In this case, \( N_q \leq \bar{N} \) is required so that the AP is able to decode the signals from active nodes with a high probability.

However, although \( |\hat{I}_q| = N_q \leq \bar{N} \) at the AP, the actual number of the active nodes in round \( q \geq 1 \), which is \( \tilde{N}_q = |\tilde{I}_q| \), can be different from \( N_q \). Thus, the scaled decision parameter \( \gamma u_q \) at each node needs to be carefully decided to make sure that \( \mathbb{E}[\tilde{N}_q] \leq \bar{N} \). In the presence of downlink errors, since \( N_q \) is no longer the number of active nodes, it is referred to as the required number of active nodes in round \( q \).

While \( \gamma u_q \) can be decided to meet \( \mathbb{E}[\tilde{N}_q] \leq \bar{N} \), there is also another important issue to be taken into account. The performance of data-aided sensing depends on the probability of MD. If the AP cannot have the measurements from the selected nodes in round \( q \geq 1 \) due to MD events, it cannot
provide a good estimate of v. Thus, it is desirable to have a low probability of MD. As shown in (30), in order to have a low probability of MD, it is required that the scaled decision parameter is less than 1 (i.e., $u_q \gamma < 1$). However, unfortunately, when the probability of MD decreases, the probability of FA increases and $\tilde{N}_q$ increases. To see this clearly, consider the average number of active nodes in round $q$ as follows:

$$
\mathbb{E}[\tilde{N}_q] = N_q (1 - P_{MD,q}) + (K - (\tilde{N}_0 + \tilde{N}_1 + \ldots + \tilde{N}_{q-1} + N_q)) P_{FA,q} \\
\leq N_q (1 - P_{MD,q}) + K P_{FA,q}. 
$$

From this, the increase of $P_{FA,q}$ (by decreasing $P_{MD,q}$) results in the increase of $\mathbb{E}[\tilde{N}_q]$. Thus, in order to avoid unsuccessful decoding in CRA, a low probability of FA is needed, which however leads to a high probability of MD and degrades the performance of data-aided sensing. This shows that the scaled decision parameter, $u_q \gamma$, becomes a key parameter to be carefully decided. That is, as $u_q \gamma$ decreases (or $u_q \gamma$ approaches $-1$), the number of FA events increases, which leads to unsuccessful CRA. On the other hand, as $u_q \gamma$ increases (or $u_q \gamma$ approaches 1), the number of MD events increases, offsetting the benefit of data-aided sensing.

**VII. Simulation Results**

In this section, simulation results for data-aided sensing are presented. For simulations, it is assumed that $\mathbf{B}^T$ consists of randomly selected $M$ column vectors of the $K \times K$ Discrete Cosine Transform (DCT) and the non-zero $S$ elements of the sparse vector $\mathbf{s}$ are either $+1$ or $-1$ (with the equal probability). To reconstruct $\mathbf{v}$ at the AP with a subset of the measurements sent by active nodes, the lasso method [32] [33] is used. That is, in each round $q$, with the data set of measurements, $\mathcal{D}_q$, the sparse signal, $\mathbf{s}_q$, is estimated using the lasso method. Note that for the sake of simplicity, CRA is not considered in simulations. However, as shown in [14], as long as the actual number of active nodes is sufficiently smaller than the length of signature sequences, $L$, CRA becomes successful. That is, in controlled access, it is assumed that the AP is able to decode signals from the requested nodes as well as those from other nodes that happen to be active (due to FA events) provided that $\tilde{N}_q \leq L - 1$. In addition, it is assumed that $\tilde{N}_q = N$ for all $q$.

Fig. 3 shows reconstruction errors at the AP with data-aided sensing and repeated random sensing after 4 rounds together with the target signal, $\mathbf{v}$, when $K = 64$, $M = 25$, $S = 3$, and $N = 5$. In the legend, RRS and DAS stand for the results of repeated random sensing and data-aided sensing, respectively. As shown in Fig. 3, data-aided sensing can provide a good estimate of $\mathbf{v}$ at the AP with $4N = 20$ measurements, while repeated random sensing cannot provide a reasonable estimate.

As mentioned earlier, the AP needs to choose active nodes using controlled access in data-aided sensing. However, due to downlink errors (i.e., MD and FA events), the AP may not be able to have the measurements from the selected nodes in $\mathcal{I}_q$, $q \geq 1$, which can degrade the performance. In particular, if there are a number of FA events, the AP can have more measurements from the nodes that are not requested to transmit than those from the nodes that are requested. Thus, it is important to take into account MD and FA events in compressive transmit request. In the rest of simulation results, the values of $\omega = \frac{P_{FA}}{P_{MD}}$ and $A_{RF}^2 N_0$ are set to -10 dB and 20 dB, respectively. In addition, $M = 100$ and $L = 64$ are fixed and a Rayleigh fading model in (28) is considered for $h_k$ in compressive transmission request.

Fig. 4 shows the (average) numbers of MD and FA events (from 1000 runs) as functions of the requested number of measurements, $N$, when $K = 300$, $L = 64$, and $\gamma u_q = 0.5$. For the theoretical approximations of the average number of MD and FA, (30) and (29) are used, respectively, in Fig. 4. It is shown that as $N$ increases, there are more FA events than MD events. For example, if $N = 50$, there are about 45 FA events and 20 MD events. This implies that the AP can only have 30 desired measurements, while 45 measurements are transmitted from the nodes that are not requested due to FA events. More importantly, the actual number of active nodes becomes $30 + 45 = 75$, which is greater than $L - 1 = 63$. Therefore, when $N$ is too large, the AP not only has more undesirable measurements, but also fails to perform CRA successfully. This implies that $\gamma$ should be carefully decided so that $\mathbb{E}[\tilde{N}_q]$ is smaller than $L - 1$ to avoid at least unsuccessful CRA.

Fig. 5 shows the (average) numbers of MD and FA events (from 1000 runs) as functions of the scaled decision parameter, $\gamma u_q$, when $K = 300$, $L = 64$, and $N = 10$. As expected, the number of MD increases and that of FA decreases when $\gamma u_q$ increases. As mentioned earlier, a large $\gamma u_q$ is required to keep the actual number of active nodes small so that CRA becomes successful. On the other hand, the benefit of data-aided sensing will diminish if $\gamma u_q$ is too large (due to a large number of MD events).

With downlink errors on compressive transmission request
(i.e., FA and MD events), the performance of data-aided sensing is shown in Fig. 6, where the mean squared error, $E[||v - v_q||^2]$, is shown in each round together with the number of active nodes in each round when $K = 300$, $N = 10$, and $S = 10$. For fair comparisons, the actual number of active nodes in each round, $\tilde{N}_q$, is assumed to be the same in data-aided sensing (with and without downlink errors) and repeated random sensing. To predict the number of active nodes, the upper-bound in (32) is considered. In Fig. 6 (a), it is shown that downlink errors degrade the performance of data-aided sensing, which is however still better than the performance of repeated random sensing. In Fig. 6 (b), the actual number of active nodes from simulations decreases as the number of round, $q$, increases However, the approximation from the theory remains unchanged as the upper-bound (i.e., (32)) is used with fixed $u_q\gamma = 0.5$ and $N = 10$ for all $q$. Note that since the actual number of active nodes is smaller than $L - 1 = 63$, successful CRA in controlled access is assumed.

Fig. 7 shows the performances of data-aided sensing and repeated random sensing for different values of $\gamma u_q$ when $K = 300$, $N = 10$, and $S = 10$ (with a fixed number of rounds, $q = 3$). As expected, as the scaled decision parameter, $\gamma u_q$, increases, the actual number of active nodes (or the number of measurements at the AP) decreases as shown in Fig. 7 (b), which results in the increase of MSE in Fig. 7 (a). Thus, for a reasonable performance, $\gamma u_q$ is to be carefully chosen (in this case, $\gamma u_q$ can be less than 0.6 as long as the actual number of active nodes per round is less than $L - 1$ for successful CRA).

In Fig. 8, the performances of data-aided sensing and repeated random sensing are shown for different numbers of the sparsity, $S$, when $K = 300$, $N = 10$, and $\gamma u_q = 0.5$ (for all $q$) with a fixed number of rounds, $q = 3$. Clearly, as the sparsity decreases, the AP can have a lower MSE. It is
noteworthy that the MSE of data-aided sensing with downlink errors (i.e., MD and FA events) can be lower than that without downlink errors as shown in Fig. 8 (a) when $S$ is small. That is, the measurements from the set of the nodes that are selected by the node selection criterion in (16) can have a higher MSE than the measurements from a slightly different set of nodes. This demonstrates that (16) does not exactly lead to the decrease of MSE (i.e., (16) is not optimal in terms of the MSE), while it is a reasonable criterion to improve the performance in general. As mentioned earlier, if the AP can have statistical properties of $v$, it can afford to find an MSE-based criterion, while (16) is applicable to any $v$ that has a sparse representation (without any knowledge of statistical properties of $v$).

Fig. 9 shows the performances of data-aided sensing and repeated random sensing for different numbers of nodes, $K$, when $N = 10$, $\gamma u_q = 0.5$ (for all $q$), and $S = 10$ (with a fixed number of rounds, $q = 3$). Since the actual number of active nodes increases with $K$ as shown in Fig. 9 (b) although $N$ is fixed (due to FA events), the MSEs of both data-aided sensing and repeated random sensing decrease with $K$ as shown in Fig. 9 (a). It is also shown that the performance gap between data-aided sensing and repeated random sensing, increases quickly when $K$ increases, which demonstrates that data-aided sensing can perform better than repeated random sensing when there are more nodes thanks to the node selection criterion.

In general, a better performance is expected with more measurements in both data-aided sensing and repeated random sensing. As shown in Fig. 10 (a), the MSEs decrease with $N$, where $K = 300$, $\gamma u_q = 0.5$ (for all $q$), and $S = 10$ (with a fixed number of rounds, $q = 3$). As mentioned earlier, the actual number of active nodes, $\tilde{N}_q$, differs from $N_q = N$, while the increase of $N$ results in the increase of $\tilde{N}_q$, which is shown in Fig. 10 (b). Thus, for successful CRA, $N$ cannot be large. It is noteworthy that according to Fig. 10 (a), a large $N$ is not required in data-aided sensing, since the MSE becomes low once $N$ is sufficiently large (say $N = 10$, which results in $E[\tilde{N}_q] \approx \frac{70}{4} = 17.5$, which is much smaller than $L - 1 = 63$ according to Fig. 10 (b)). In other words, with a smaller number of measurements, data-aided sensing can perform better than repeated random sensing thanks to the node selection criterion.

### VIII. CONCLUDING REMARKS

In this paper, data-aided sensing was studied as a cross-layer approach to collect data (or measurements) from IoT devices based on the notion of CS when measurements have a sparse representation. A node selection criterion was proposed to choose certain nodes in iterations for data-aided
sensing and it was shown that CRA plays a crucial role in collecting measurements efficiently. ERRoneous decisions at nodes and their impact on the performance have also been investigated when the AP sends compressed transmission request. Simulation results have shown that data-aided sensing outperforms repeated random sensing thanks to active node selection through iterations. In addition, it was demonstrated that although there are downlink decision errors at nodes on transmission request, their impact on the performance can be negligible as the number of nodes increases and/or the sparsity of the target signal is sufficiently low.

In this paper, data-aided sensing was applied to signals that have sparse representations. As a further work, a generalization of data-aided sensing to signals that do not have sparse representations might be studied. It is also interesting to extend the notion of data-aided sensing to the upper layers and generalize it. Furthermore, distributed data-aided sensing would be an important issue to support a large of devices/sensors.

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