BLOCK COMPRESSED SENSING BASED DISTRIBUTED RESOURCE ALLOCATION FOR M2M COMMUNICATIONS

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ABSTRACT

In this paper, we utilize the framework of *compressed sensing* (CS) for device detection and distributed resource allocation in large-scale *machine-to-machine* (M2M) communication networks. The devices are partitioned into clusters according to some pre-defined criteria, e.g., proximity or service type. Moreover, by the sparse nature of the event occurrence in M2M communications, the activation pattern of the M2M devices can be formulated as a particular block sparse signal with additional in-block structure in CS based applications. This paper introduces a novel scheme for distributed resource allocation to the M2M devices based on block-CS related techniques, which mainly consists of three phases: (1) In a full-duplex acquisition phase, the network activation pattern is collected in a distributed manner. (2) The base station detects the active clusters and the number of active devices in each cluster, and then assigns a certain amount of resources accordingly. (3) Each active device detects the order of its index among all the active devices in the cluster and accesses the corresponding resource for transmission. The proposed scheme can efficiently reduce the acquisition time with much less computation complexity compared with standard CS algorithms. Finally, extensive simulations confirm the robustness of the proposed scheme under noisy conditions.

Index Terms— Compressed sensing, block sparse, distributed resource allocation, M2M communications.

I. INTRODUCTION

Towards the next generation of mobile and wireless networks, *machine-type communications* (MTC) [1] is expected to play a significant role and form the basis for the future *Internet of Things* (IoT). However, the number of M2M devices in a network can potentially be very large, thus posing serious challenges to the radio access network. In LTE, a device accesses the network by firstly sending a preamble to indicate its active status, followed by a resource allocated by the serving *base station* (BS) based on the detection [2]. Nevertheless, for large-scale communications like MTC, distributed resource allocation schemes are proposed due to their better scalability with the size of the network [3].

Apart from a huge number of devices, the messages in M2M communication scenarios are in general highly correlated due to proximity, the same service type, and etc [4]. As a result, it is reasonable to partition the devices into a number of clusters. Moreover, since the MTC traffic is characterized by the sporadic communication among a huge number of devices, each M2M device has a low probability of being active, thus exhibiting a certain level of sparsity in the detection activity. Recognizing the cluster-like behavior and the sparsity in the activation pattern among the M2M devices, the detection problem can be formulated as a particular block sparse signal recovery problem [5]-[7] – with additional in-block structure – in the *compressed sensing* (CS) based applications, where the signal acquisitions can be done in a significantly reduced sampling rate [8]-[10].

Motivated by the CS principles [11], we propose in this paper a novel distributed detection scheme of the network activation pattern to facilitate distributed resource allocation strategies for large-scale M2M communications. Our scheme mainly consists of three phases:

(i) In the acquisition phase, all devices transmit simultaneously pre-equivalized individual sequences, each of which indicating the membership to a particular cluster. Exploiting full-duplex transceivers, all the devices and the BS receive individual linear combinations. A similar scheme has already been investigated in [12] for CSI feedback reduction.

(ii) The BS then detects the active clusters and the number of active devices in each cluster. Then it broadcasts this information to the devices and assigns a certain amount of resources accordingly.

(iii) Each active device detects the order of its index among all the active devices in the cluster and accesses the corresponding resource for transmission.

A novel algorithm based on the Count-Sketch procedure [13] is developed for the realization of phase (ii). Phase (iii) is performed based on some conventional greedy algorithms such as *Orthogonal Matching Pursuit* (OMP) [15] or *Iterative Hard Thresholding* (IHT) [16] but with side information of the feedback from the BS to reduce the number of iterations. Theoretical evaluations show that the proposed scheme is able to efficiently reduce the acquisition time with much less computation complexity. For a K-sparse signal of length N and block-size d, $O(K \log d)$ distributed measurements are sufficient for robust support recovery for the proposed algorithms, which is much less when compared with $O(K \log N)$ required by conventional CS recovery algorithms like Basis Pursuit (BP) [17] or OMP. Finally, extensive simulations confirm the robustness of the proposed scheme in the presence of Gaussian noise and inaccurate channel estimations.

The remainder of this paper is organized as follows. Section II describes the system model and formulates the problem. In Section III, the proposed distributed resource allocation scheme is discussed in detail. Numerical results are presented and evaluated in Section IV. Finally, Section V concludes the paper with some final remarks.

II. SYSTEM MODEL

II-A. Transmitter Side

Consider an M2M network with N devices, which are partitioned in advance into L clusters of equal size d according to some pre-defined criteria. A cluster is said to be "active" if one or more devices from the same cluster are active. We define a twofold sparsity pattern to model the active status of the M2M devices, namely the *block-sparsity* K_B and *in-block-sparsity* K_I. That is, only K_B out of L clusters are active, and the number of active devices in each cluster is at most K_I. Therefore, the total number of active devices in the network is $K \leq K_B K_I$. Due to the sparse nature of the event occurrence in MTC, we have $K \leq K_B K_I \ll N = Ld$. Herein, we denote a K-sparse binary sequence $x \in \mathbb{B}^N$ as the status vector of our interest, with entry "1" indicating a device is active and "0" otherwise. Furthermore, we denote $x_\ell \in \mathbb{B}^d, \ell \in \{1, \cdots, L\}$ as the status vector for cluster ℓ. In addition, the *block support*, denoted as $\mathcal{S}_B$, is defined to be the set of index of the active clusters: $\mathcal{S}_B = \{\ell \in \{1, \cdots, L\} : ||x_\ell||_0 \neq 0\}$. Similarly, the *in-block support*, denoted as $\mathcal{S}_{I,\ell}$, indicates the set of indices of the active devices in cluster ℓ: $\mathcal{S}_{I,\ell} = \{j \in \{1, \cdots, d\} : x_{\ell,j} = 1\}$. Since x is K_B block sparse and K_I in-block sparse, we have $|\mathcal{S}_B| = K_B$ and $|\mathcal{S}_{I,\ell}| \leq K_I$ for all $\ell \in \{1, \cdots, L\}$.

We apply the CS theory to the transmission incurred by the M2M devices in the network. To this end, let $A \in \mathbb{R}^{M \times N}$ be the measurement matrix whose exact structure is defined later in Section III. Each column of A, say column i denoted by $a_i, i \in \{1, \cdots, N\}$, corresponds to the signature sent by M2M device i if it is active. Besides, we denote $A_\ell \in \mathbb{R}^{M \times d}$ as a submatrix of A corresponding to the signatures sent by the devices from the ℓ-th cluster.

II-B. Receiver Side

The signal $y \in \mathbb{C}^M$ received by the BS at some given time instant is given by

$$y = AH_B x + \epsilon, \tag{1}$$

where $H_B \in \mathbb{C}^{N \times N}$ is the diagonal channel matrix, and $\epsilon \in \mathbb{C}^M$ is the thermal noise vector having random, zero-mean components of variance σ^2.

We assume that the cluster structures are known both at the BS side and at all the M2M devices. Furthermore, all the nodes in the network have the channel information from other nodes to itself as well as from itself to the BS. In addition, the network is assumed to support full-duplex mode. Thus, besides the global measurement obtained at the BS, the active devices also have their own local measurements during acquisition phase (i).

We apply the CS theory in our proposed distributed resource allocation scheme to reconstruct the K-sparse signal x from the received signal y at the BS by using M measurements. As discussed in Section I, on one hand, the BS has to detect the number of active clusters as well as the number of active devices in each cluster; and on the other hand, each active device needs to detect the order of its index among all the active devices in the cluster with its local measurement and the feedback information from the BS. Herein, mapping to the mathematical model, our object of interest would be to perform the block support recovery at the BS and the in-block support recovery at each active device. To be specific, the goal is to obtain an accurate estimate of $\mathcal{S}_B$ and $|\mathcal{S}_{I,\ell}|$ for all $\ell \in \{1, \cdots, L\}$ at the BS, and thereafter, an accurate estimate of $\mathcal{S}_{I,\ell}$ at each active device from cluster ℓ.

III. DISTRIBUTED RESOURCE ALLOCATION FOR M2M

In this section, we propose a novel block CS based recovery algorithm to solve the target problems for distributed resource allocation in large-scale M2M communication networks. As discussed in Section II-B, it consists of two major phases, the block support recovery at the BS and the in-block support recovery at the active devices, respectively. Due to complexity reasons, convex methods [17] are mainly prohibited in such applications. Therefore we will apply some sketching and greedy algorithms for our proposed approach.

III-A. Block Support Recovery at BS

The measurement matrix $A \in \mathbb{R}^{M \times N}$ in (1) that we use here is a structured random matrix, which is an extension of those utilized by the Count-Sketch procedure proposed in [13][14]. We denote by $\mathcal{A}(R, T, L, d, \alpha)$ a particular distribution over matrices having RT rows and Ld columns (to be described below), and we assume that the measurement matrix A is drawn from this distribution, i.e., $A \sim \mathcal{A}(R, T, L, d, \alpha)$.

The measurement matrix A is composed of the vertical concatenation of T individual random matrices, denoted $A_t \in \mathbb{R}^{R \times N}$ for $t \in \{1, \cdots, T\}$. Meanwhile, each A_t consists the horizontal concatenation of L sub-matrices $A_{t,\ell} \in \mathbb{R}^{R \times d}$ for $\ell \in \{1, \cdots, L\}$. Each $A_{t,\ell}$ is a sparse matrix containing exactly d non-zero components - located on the same row and with the same value. The index of the row with non-zero elements is chosen uniformly at random from the set $\{1, 2, \cdots, R\}$, and the non-zero component takes the value of $\pm\alpha$ with probability $1/2$. For a given realization of $A_{t,\ell}$, let $h_{t,\ell} \in \{1, \cdots, R\}$ denote the index of the row of $A_{t,\ell}$ that has the non-zero entries, and $s_{t,\ell} \in \{-\alpha, +\alpha\}$ be the corresponding value of the non-zero components in $A_{t,\ell}$.

For illustration, suppose that the measurements are obtained at the BS with noise-free transmission $y = AH_B x$. Since perfect channel knowledge H_B is assumed to be known both at the BS and at the devices, we can take, for instance, the pseudo inverse of the channel matrix H_B^+ at the transmitter side. Assuming full rank channel matrix, the obtained measurements at the BS are given as

$$y = AH_B H_B^+ x = Ax. \tag{2}$$

We denote y_t as the subvector of y corresponding to observations obtained via the submatrix A_t, i.e., $y_t = A_t x$, for $t \in \{1, \cdots, T\}$. The extended Count-Sketch procedure is implemented as follows. For $t \in \{1, \cdots, T\}$, form the signal estimates $\tilde{x}_t \in \mathbb{R}^N$ by indexing and scaling the entries of the corresponding observations y_t, where $\tilde{x}_t = A_t^T y_t$. Then the individual entries of $\tilde{x}_t$ are given as $\tilde{x}_{t,i} = s_{t,\ell} y_{t,h_{t,\ell}}$ for $i \in \{1, \cdots, N\}$, if x_i belongs to the ℓ-th block. Thereafter, we form a signal estimate $\hat{x}$ whose entries are given by

$$\hat{x}_i = \text{median}\{\tilde{x}_{t,i}\}_{t=1}^T, \quad \text{for} \quad i \in \{1, 2, \cdots, N\}. \tag{3}$$

In other words, each entry of the signal estimate is obtained as the median of the corresponding entries of the estimates $\tilde{x}_t$. Similarly, the block-wise estimate $\bar{x}_\ell$ can be obtained as

$$\bar{x}_\ell = \text{median}\,\{\hat{x}_i\}_{i=d\ell-d+1}^{d\ell}\,, \quad \text{for} \quad \ell \in \{1, 2, \cdots, L\}. \tag{4}$$

The rationale for using the extended Count-Sketch algorithm for block support recovery is illustrated as follows. For a given x_i from block $\ell \in \mathcal{S}_B$, the estimate $\tilde{x}_{t,i}$ corresponds exactly to the signals from block ℓ whenever $h_{t,\ell}$ is distinct from $h_{t,\bar{\ell}}$, for all $\bar{\ell} \in \mathcal{S}_B \backslash \ell$. Conditioned on this, we have

$$\begin{aligned}\tilde{x}_{t,i} &= s_{t,\ell} y_{t,h_{t,\ell}} = s_{t,\ell}\left(\sum_{i=1}^{d} s_{t,\ell} x_i\right) = s_{t,\ell}^2 \left(\sum_{i=1}^{d} x_i\right) \\ &= \alpha^2 |\mathcal{S}_{I,\ell}|,\end{aligned} \tag{5}$$

where the second step follows from the structure of $A_{t,\ell}$ with equal non-zero elements on the same row, and the last step follows since $x_i \in \{0, 1\}$ is drawn from a binary ensemble. Thence, each estimation $\tilde{x}_{t,i}$ of x_i from the ℓ-th blcok corresponds to $|\mathcal{S}_{I,\ell}|$ - the ultimate goal for block support recovery at the BS. By taking the median value block-wisely among all individual estimations as (4), the size of the in-block support set $|\mathcal{S}_{I,\ell}|$ can be obtained as

$$|\mathcal{S}_{I,\ell}| = \left[\frac{1}{\alpha^2} \cdot \bar{x}_\ell\right], \quad \text{for} \quad \ell \in \{1, 2, \cdots, L\}. \tag{6}$$

Therefore, since $|\mathcal{S}_{I,\ell}|$ indicates the number of active devices in cluster $\ell \in \{1, 2, \cdots, L\}$, those clusters with $|\mathcal{S}_{I,\ell}| > 0$ are marked as "active" and detected by the BS.

Now we analyze the probability of the conditions for (5) to hold. For a particular $t \in \{1, \cdots, T\}$ and a given x_i from block $\ell \in \mathcal{S}_B$, notice that the estimate $\tilde{x}_{t,i}$ will corresponds exactly to $|\mathcal{S}_{I,\ell}|$ *iff* $h_{t,\ell}$ is distinct from $h_{t,\bar{\ell}}$ for all $\bar{\ell} \in \mathcal{S}_B \backslash \ell$. Conditioned on this, we form a particular submatrix of A_t realized by the horizontal concatenation of submatrices $A_{t,\bar{\ell}}$ for all $\bar{\ell} \in \mathcal{S}_B \backslash \ell$. For any of such realizations to ensure the conditions for (5), since $|\mathcal{S}_B| = K_B$, there are at most $R - (K_B - 1)$ out of R allowable choices for the row index of $A_{t,\ell}$ where the entries are non-zero. Furthermore, these choices are equally likely since the index of rows with non-zero entries are drawn uniformly at random. Therefore, we have

$$\mathbb{P}\left(\tilde{x}_{t,i} = \alpha^2 |\mathcal{S}_{I,\ell}|\right) \geq \frac{R - K_B - 1}{R}. \tag{7}$$

As shown in [13], by applying the union bound to ensure the conditions for (5) for all $\ell \in \{1, \cdots, L\}$, it leads to a requirement of $R = O(K_B)$ and $T = O(\log L)$ to guarantee the block support recovery at the BS with overwhelming probability.

III-B. In-block Support Recovery at Devices

After the BS detects the active clusters in the network and the number of active M2M devices in each active cluster (without knowing exactly which one), it broadcasts this information to the devices and assigns a certain amount of resources accordingly; thus those active devices can use this feedback as side information for the in-block support recovery.

During the acquisition phase, each active device also simultaneously collects its own local measurements. Herein, by taking the matrix for the transmit signatures defined in (2), the local measurements obtained at an active device are given by

$$y_D = A H_I H_B^+ x + \epsilon = \tilde{A} x + \epsilon, \tag{8}$$

where H_I is an $N \times N$ matrix representing the wireless channels between the M2M devices.

As introduced in Section III-A, for a given cluster $\ell \in \{1, \cdots, L\}$, the corresponding submatrix A_ℓ has only T rows with non-zero components, whose index are denoted by the set D_ℓ. Thus, in order to perform the in-block support recovery of x_ℓ, we simply need to focus on $y_{D,\ell}$ – a vector composed of the entries of y_D corresponding to D_ℓ, which is given as

$$y_{D,\ell} = \tilde{A}_{D,\ell} x_\ell + \tilde{\epsilon}, \tag{9}$$

where $\tilde{A}_{D,\ell}$ is a $T \times d$ submatrix of $\tilde{A}$ with vertical concatenation of the rows corresponding to D_ℓ and columns for block ℓ. Besides, $\tilde{\epsilon}$ comprises the interference from other clusters and thermal noise at the corresponding entries of $y_{D,\ell}$.

With the randomness in $\tilde{A}_{D,\ell}$ introduced by the channels between devices, which are assumed to be i.i.d Gaussian, we can use some conventional greedy algorithms such as OMP [15] or IHT [16] to perform the in-block support recovery. Moreover, since we have the feedback information from the BS on the number of active devices $|\mathcal{S}_{I,\ell}|$ in the cluster, the number of iterations needed for implementing the greedy algorithms can be greatly reduced and limited to $|\mathcal{S}_{I,\ell}|$.

In [8] and [10], it has been proved that if the measurement matrix is an i.i.d. Gaussian matrix or random ± 1 entry matrix, then a K-sparse signal can be reliably reconstructed with the CS methods if the number of measurements $M \geq cK \log N$, where c is a constant. For our specific problem, since the signal x_ℓ of interest is of dimension d and with sparsity level K_I, the support can be recovered with high probability if the number of effective measurements satisfies

$$T = cK_I \log d = O(K_I \log d). \tag{10}$$

III-C. Comparisons with Existing Solutions

Many contributions have been proposed for the device detection in large-scale MTC networks by employing the CS theory. In [18], Meng *et.al* simply adopted the detection algorithms from the probabilistic Bayesian framework for the sparse event detection in *wireless sensor networks* (WSN). In [19], the authors applied some greedy CS detection algorithms for jointly decoding the multi-user activity and data in *Code Division Multiple Access* (CDMA) systems, where the exploit of the CS theory can greatly reduce the length of the spreading sequences, thus leading to a lower symbol rate. However, both of the schemes are targeted for centralized detection at the receiver side, whereas our focus is on distributed detection and resource allocation schemes for the M2M devices.

Besides, the authors in [20] proposed a sparse signal recovery scheme via decentralized in-network processing for event detection in WSN based on a consensus optimization formulation. However, since the authors apply the random sleeping strategy in order to enforce the compressive data collection, the detection field for each active time slot is rather uncertain and may end in wrong detections with a high probability. In our proposed scheme, both the block and the in-block sparsity in the M2M activation pattern are exploited, and the performance is highly reliable as will be shown later in Section IV.

As discussed in Section III, our target problem can be mapped to a support recovery procedure for a block-sparse signal with block sparsity K_B and in-block sparsity K_I. For a given realization of the measurement matrix, there are certain requirements on the number of measurements needed for the reliable signal reconstruction. In general, $R = O(K_B)$ and $T = O(\log L)$ are sufficient for the block support recovery at the BS, and $T = O(K_I \log d)$ measurements are required for the in-block support recovery at the devices. Thus, the overall number of distributed measurements $M = RT$ required by the proposed scheme is $O(\max\{K_B \log L, K_B K_I \log d\})$. However, if the signal is treated as a conventional K-sparse vector as in [10] without exploiting knowledge of the block-sparse structure, where $K = K_B K_I$, a sufficient condition for perfect recovery using OMP is $M = O(K \log N) = O(K_B K_I \log N)$. Since $d \ll N$, we can see that from the scaling point of view, less measurements are need by the proposed scheme. Moreover, compared with conventional OMP which requires at least K iterations for the signal recovery, having distributed processing reduces the number of iteration to K_I for the guaranteed performance, which leads to significantly reduced computational complexity.

IV. NUMERICAL RESULTS

We conduct extensive simulations to verify the performance of the proposed distributed device detection and resource allocation scheme. In our experiments, we take the number of M2M devices in the network to be $N = 10000$ and they are partitioned into $L = 100$ clusters with equal size $d = 100$. The sparsity level is set to be $K = 20$, with block sparsity $K_B = 4$ and in-block sparsity $K_I = 5$, respectively, i.e., $K = K_B K_I$. Thus, the target problem is to reconstruct the K-sparse binary vector of length N from M distributed measurements obtained via the measurement matrix which is drawn from the distribution $\mathcal{A}(R, T, L, d, \alpha)$ as defined in Section III-A.

Figure 1 depicts the detection probability as a function of the number of measurements, for both OMP with Gaussian measurements and the proposed algorithm. For each parameter sets we average over 1000 pairs of realizations of the measurement matrix and the block-sparse signal. We can see that the proposed scheme performs a little bit worse than the standard OMP algorithm with Gaussian measurements in the noise-free case. Though we have analyzed in Section III-C that the proposed scheme requires less measurements from the scaling point of view, the constant c in (10) is comparatively larger for distributed processing. We also evaluate the performance of the proposed scheme under inaccurate channel estimation and white Gaussian noise. Since the imperfect channel knowledge is taken as noise in the signal processing, we limit the *signal-to-noise ratio* (SNR) to 5 dB in the simulations. The corresponding results, also depicted in Figure 1, show that our approach outperforms the standard OMP algorithm with Gaussian measurements, indicating more robustness in performance against noise and inaccurate channel estimations.

Figure 2 plots the CDF of the average number of iterations for the signal recovery. It can be obviously shown that the proposed scheme significantly outperforms the standard OMP algorithm by requiring much less iterations due to distributed processing among the clusters, thus leading to greatly reduced computational complexity.

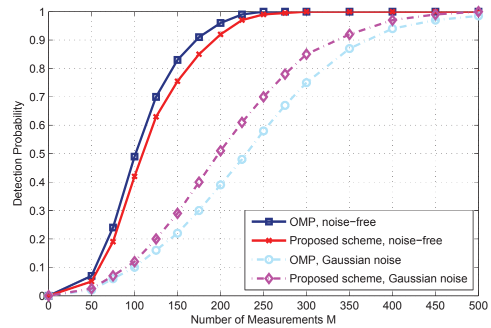

Fig. 1. Simulation results on the detection probability

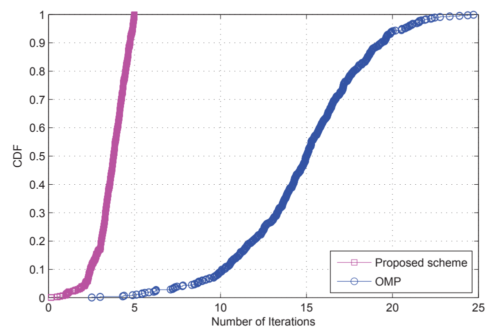

Fig. 2. CDF of the average number of iterations

V. CONCLUSION

In this paper, we introduced a novel scheme for device detection and distributed resource allocation in large-scale M2M communication networks based on block CS related techniques. We partition the M2M devices in the network into clusters based on some pre-defined criteria. By exploiting the twofold sparsity in the activation pattern of the M2M devices, i.e., the block sparsity and in-block sparsity, the target problem is mapped into a support recovery procedure for a block-sparse signal in the CS theory. The proposed scheme mainly consists of three phases: Firstly, in the acquisition phase, network activity is collected in a distributed fashion. Secondly, the BS detects the active clusters and the number of active devices in each cluster, and then assigns a certain amount of resources accordingly. Finally, each active devices detects the order of its index among all the active devices in the cluster and accesses the corresponding resource for transmission. It has been verified that the proposed scheme is able to efficiently reduce the scaling of the required number of measurements for reliable signal recovery and with much less computational complexity when comparing with conventional CS reconstruction algorithms like OMP with Gaussian measurements. Moreover, extensive simulations also confirm the robustness of the proposed scheme against Gaussian noise and inaccurate channel estimations.

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