A Method for Co-existing Heterogeneous IoT Environments based on Compressive Sensing

Hyungkeuk Lee, Seng-Kyoun Jo, NamKyung Lee and Hyun-Woo Lee

***Abstract*—Compressive Sensing (CS) is a stable and robust technique that allows for the sub-sampling of data at a given data rate: 'compressive sampling' or 'compressive sensing' at rates smaller than the Nyquist sampling rate. It makes it possible to create standalone and net-centric applications with fewer resources required in Internet of Things (IoT). CS-based signal and information acquisition/compression paradigm combines the nonlinear reconstruction algorithm and random sampling on a sparse basis that provides a promising approach to compress signal and data in information systems. In this paper, we investigates how CS can provide new insights into coexisting heterogeneous IoT environments. First, we briefly introduce the CS theory with respect to the sampling through providing a compressed sampling process with low computation costs. Then, a CS-based framework is proposed for IoT, in which the hub nodes measure, transmit, and store the sampled data into the fusion center. Then, an efficient cluster-sparse reconstruction algorithm is proposed for in-network compression aiming at more accurate data reconstruction and lower energy efficiency. Therefore, compression should be performed locally at each Access Point (AP) and reconstruction is executed jointly to consider dependencies in the acquired data by the final fusion center.**

***Index Terms*—Compressive Sensing (CS), Internet of Things (IoT), Wireless Sensor Networks (WSNs), Fusion Center**

I. INTRODUCTION

Internet of Things (IoT) environment is expected to grow tremendously in a few decades, thereby posing new challenges for both existing Information Communication Technology (ICT), designed with human communication in mind. Researchers found that, in information systems, Wireless Sensor Networks (WSNs) and IoT, many types of information have a property called sparseness in the transformation process which allows a certain number of samples enabling capturing all required information without loss of information [1]. IoT has emerged as a technological revolution in the information industry. IoT is expected to be a worldwide network of interconnected objects, and its development depends on a number of new technologies, such as WSNs, cloud computing, and information sensing [2]. In IoT-based information systems, a low-cost data acquisition system is necessary to effectively collect and process the data and information at IoT end nodes. WSNs have the potential of a wide range of applications in many industrial systems. WSNs can be integrated into the IoT, which consists of a number of interconnected sensor nodes [3].

An IoT can involve thousands of independent components including computers, sensors, RFID tags, or mobile phones, all are capable of generating and communicating data, in which many techniques are involved for data collection, transmission, and storage. In IoT, a desirable data compression ratio is very important, which cannot be obtained by current methods without introducing unacceptable distortions. Furthermore, for most data compression solutions in IoT, three main problems must be solved: resolution, sensitivity, and reliability. This reality has driven much of the recent research on compressive data acquisition, in which data is acquired directly in a compressed format [4]. Recovery of the data typically requires finding a solution to an undetermined linear system, which becomes feasible when the underlying data possesses special structure. Compressive Sensing (CS) is a stable and robust technique that allows for the sub-sampling of data at a given data rate: 'compressive sampling' or 'compressive sensing' at rates smaller than the Nyquist sampling rate [5][6]. The theory of CS states that if a signal is sparse in a transform domain, then it can be reconstructed exactly from a small set of linear measurements using tractable optimization algorithms. The CS changes the rules of data acquisition in information systems by exploiting a priori data sparsity information. The applications of CS for data acquisition in WSNs have been studied recently [7]. Authors in [7] investigated CS for networked data in WSNs through considering the distributed data sources and their sampling, transmission, and storage.

However, for the first time, our work studies information acquisition in IoT with CS from the perspective of data-compressed sampling, robust transmission, and accurate reconstruction to reduce the energy consumption, computation costs, and data redundancy and increase the network capacity. A common task of an IoT end node is to transmit the sensed data to a specific node or fusion center (FC); however, how to efficiently acquire, store, and transmit among a large number of source nodes remains a challenge. It is obvious that various IoT environments or platforms should co-exist with other IoT ones in the real life, because tremendous IoT devices and platforms come out nowadays. In this paper, assume that multiple IoT platforms are utilized simultaneously, we describe that how can huge amounts of information from those IoT device be handled with at the same time.

II. COMPRESSIVE SENSING

Each node acquires i.i.d. signals. In this scenario, the compressed sensing can be used to effectively reduce the sampling rate without degenerating the reconstruction performance. A k-sparse signal $\mathbf{x} \in \mathbb{R}^n$ can be completely described by the k nonzero components. $\mathbf{x}$ can be sampled with a diversifying

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matrix and a measurement vector $\mathbf{y}$ can be obtained. The sampling process can be described as

$$\mathbf{y} = \mathbf{A}\mathbf{x} + \boldsymbol{\epsilon} \tag{1}$$

in which $\mathbf{A}$ denotes an $m \times n$ measurement matrix and $\boldsymbol{\epsilon}$ is a noise term.

Then benefits of this model are: 1) the number of samples generated by each node can be significantly reduced without losing the reconstruction accuracy; 2) it may cause the significant reduction of communications over the networks; and 3) the computation cost at nodes can be reduced.

In IoT networks, the measurement $\mathbf{y}$ can be represented as

$$\mathbf{y} = [y_1, \cdots, y_m]^T = \sum_{j=1}^{n} A_{i,j} x_j \tag{2}$$

in which y_m can be easily represented as a linear combination of the sparsely represented signal x_i.

Each node is able to compute x_j by multiplying the corresponding element of matrix $A_{i,j}$, which can be constructed by choosing the entries as i.i.d realizations from some probability distribution. Then, randomized gossip is used to aggregate the $A_{i,j}x_j$ on a fusion center. In this way, $\mathbf{y}$ is available at the fusion center. Considering that a network with n nodes at location $\{p_i\}$, $i = i, \cdots, n$ is monitoring multiple events, assume that $\mathcal{N}_a(t)$ nodes are in active mode and $\mathcal{N}_s(t)$ nodes are in sleep mode at time t. Let x_i denote the source value at p_i, $i \in n$. Then, measurement y_i od node i can be represented as

$$y_i = \sum_{j \in N} A_{j,i} x_j + \epsilon_i \tag{3}$$

in which $A_{i,j} = A_{i,j}$ is the influence of this event on sensor point p_i, and ϵ_i is the random measurement noise of zero mean. Here, $\mathbf{x}$ is sparse and $A_{i,j}$ can be learned during the network deployment stage.

Assume that the influence $A_{j,i} = 0$, if the distance from j to i is larger than the communication range. Then, the measurement y_i becomes $y_i = x_i + \sum_{j \in n} A_{j,i} x_j + \epsilon_i$, furthermore, for the active nodes in the network, we have

$$\mathbf{y}_a = \mathbf{\Phi}\mathbf{A}\mathbf{x} + \boldsymbol{\epsilon}_a \tag{4}$$

where $\mathbf{A}$ is the $n \times n$ matrix where the (i, j)th element is $(A_{i,j})$, $\mathbf{\Phi}$ is the $m \times n$ measurement matrix that selects the m rows of $\mathbf{A}$ corresponding to the active sensors, and $\mathbf{y}_a$ and $\boldsymbol{\epsilon}_a$ are the $m \times 1$ measurement and noise vectors, respectively.

III. The Proposed System

Here, a CS framework for signal or data acquisition in the heterogeneous IoT platforms will be introduced. It acquires a pre-defined continuous packets sequence of data per interval with respect to a type of device, and after a compressed sensing-based encoding procedure the encoded packets are transmitted by wireless communications. The proposed CS-based IoT system simplifies all end (or edge) components as IoT nodes, as shown in Fig. 1. The proposed system contains of three phases: 1) the design of compressed sensing information end-node, which aims to reduce the sampling rate and the number of samples without losing the essential information; 2) the compressed data delivery scheme, in which compressed data are delivered to IoT networks to minimize the received data distortion and communication burden; and 3) data reconstruction and analysis at fusion centers. The CS-based IoT system is a flexible architecture to implement a range of different information acquisition in IoT.

The essential goal of IoT systems is to accurately acquire the information about events of interest [8]. The information acquisition networks usually consist of three core components: 1) an information sensing system, which can detect and compressively sample the signals of events; 2) compressed sampling, in which the systems sample information that are preconditioned and transmitted over the networks; and 3) reconstruction algorithms, in which the system accurately reconstructs the original signal from the compressed samples. Inadequate sampling may cause aliasing in signal reconstruction when the measurement matrices are not properly selected. In contrast to conventional sensing and sampling systems, the CS can extend them to a much broader class of signals. The CS-based sampling process works by taking a small number of samples of a compressible signal on a sparse basis to reconstruct the original signals by using linear/convex optimization methods. The CS theory typically requires the projection matrix to be random, though in practice researchers have often found that the same idea can be used in other conventional sampling scenarios.

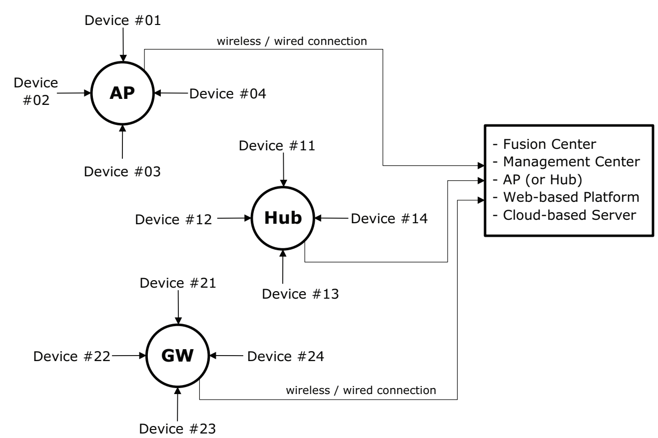

Fig. 1: An example of co-existing various IoT systems.

Figure 1 represents an example of the proposed system's snapshot. Besides being somewhat different among many IoT platforms, each has generally a typical structure, which comprises of an end device, a hub and a fusion center. The end device captures information according to its own purpose, the hub takes charge of gathering data from many device and forwards it to the fusion center. Finally, all of data is conveyed to a fusion center which processes, manages and analyzes it, respectively. At the middle point, the hubs are called differently with respect to IoT platforms, i.e., hub, AP (Access Point) or GW (Gateway). In the same manner, the fusion center can be called by management center, AP, hub, web-based platform or cloud-based server, etc., according to IoT platforms.

In general, each AP gets information $\mathbf{x}_A$ within a certain time slot made by concurrent signals x_1, x_2, and x_{N_A} from devices, as follows

$$\mathbf{x}_A = [x_1, x_2, \cdots, x_{N_A}]^T \quad (5)$$

where N_A is the number of devices belonging to the AP. Before delivering $\mathbf{x}_A$, our method apply information delivering to the fusion center in IoT and WSNs with CS from the perspective data-compressed sampling, robust transmission, and the accurate reconstruction. Assumed that $\widehat{\mathbf{\Phi}}_A = \mathbf{\Phi}_A \mathbf{\Psi}_A^{-1}$, $\mathbf{x}_A$ can be measured as

$$\mathbf{y}_A = \widehat{\mathbf{\Phi}}_A \mathbf{x}_A = \mathbf{\Phi}_A \mathbf{\Psi}_A^{-1} \mathbf{x}_A = \mathbf{\Phi}_A \boldsymbol{\alpha}_A, \quad (6)$$

where $\mathbf{\Psi}_A^{-1}$ is the transformation, which could be a wavelet transform, the signal $\mathbf{x}$ can be represented as K-sparse data only if $K \ll N$ entries of $\boldsymbol{\alpha}$ are nonzero, and $\mathbf{\Phi}$ is an $M \times N$ random measurement matrix, $\mathbf{\Phi} \in \mathbb{R}^{M \times N}$ to satisfy the Restricted Isometry Property (RIP) [4].

Since each AP (or Hub, GW) has its own random matrix, each data is encoded separately and is delivered to the fusion center. The fusion center can be reconstructed

$$\begin{bmatrix} \mathbf{y}_A \\ \mathbf{y}_H \\ \mathbf{y}_G \end{bmatrix} = \begin{bmatrix} \widehat{\mathbf{\Phi}}_A & & \\ & \widehat{\mathbf{\Phi}}_H & \\ & & \widehat{\mathbf{\Phi}}_G \end{bmatrix} \begin{bmatrix} \mathbf{x}_A \\ \mathbf{x}_H \\ \mathbf{x}_G \end{bmatrix} + \begin{bmatrix} \boldsymbol{\epsilon}_A \\ \boldsymbol{\epsilon}_H \\ \boldsymbol{\epsilon}_G \end{bmatrix} \quad (7)$$

If some IoT environments have more importance than other IoT devices (wellness devices such as heart rate monitoring, photoplethysmographic wristband are more critical than humidity, thermometer with respect to purposes), the fusion center could consider this importance when reconstructing delivered data from heterogeneous IoT platforms. Borrowing the concepts from [9], we introduce an importance to measurement matrix per each AP with respect to different kinds of IoT devices or IoT platforms.

The measurement matrix for weighted CS is obtained by multiplying the weight matrix $\mathbf{w}$ (calculated in view of reconstruction, which is beyond the scope of this paper) by the random and transform matrices. Weighted CS samples the multi-view image signals more compressively for a given reconstruction quality since the measurement matrix is expressed as

$$\mathbf{y}_A^{\mathbf{w}} = \widehat{\mathbf{\Phi}}_A^{\mathbf{w}} \mathbf{x}_A = \mathbf{\Phi}_A \mathbf{w} \mathbf{\Psi}^{-1} \mathbf{x}_A = \mathbf{\Phi}_A \mathbf{w} \boldsymbol{\alpha}_A. \quad (8)$$

The CoSaMP algorithm [10] guarantees the same performance as the best optimization-based CS recovery approaches. Each image from a sensor node has a different weight. As such, it is advisable to also focus on each image's weight and amplitude on the decoder side to achieve an optimized weighted CS. Since CoSaMP guarantees that the performance for robust recovery follows the best convex optimization approach, we modified this state-of-the-art CS recovery algorithm using weighted CS.

After applying weighted CS encoding to each AP separately, the weighted CS scheme reconstructs each piece of data according to its own importance on the decoder side, if the weight matrix $\mathbf{w}$ is an identity matrix $\mathbf{I}$ when the weight is not considered. The weighted CoSaMP algorithm sequentially selects the most important element with respect to the weight rather than its own amplitude. The detailed weighted CoSaMP procedure is described in Table I. All of the steps are identical to those of CoSaMP, except for the stages of 'identification' and 'pruning'; the weighted CS decoder applies reconstruction weighting in those stages. We define $\mathbb{W}(\boldsymbol{\alpha}, K)$ as an algorithm that obtains the best K-approximation of $\boldsymbol{\alpha}$ in the subspaces

$$\mathbb{W}(\boldsymbol{\alpha}, K) = \arg \min_{\boldsymbol{\alpha}_K \in \Sigma_K} \mathbf{w} \|\boldsymbol{\alpha} - \boldsymbol{\alpha}_K\|_2. \quad (9)$$

TABLE I: Weighted CoSaMP algorithm

Input: $M \times N$ matrix $\mathbf{\Phi}$, sample vector $\mathbf{y} = \mathbf{\Phi}\boldsymbol{\alpha} + \epsilon$ and sparsity of K, weight vector $\mathbf{w}$
Output: K-sparse approximation $\mathbf{a}$ of $\boldsymbol{\alpha}$

1: $\mathbf{a}^0 \leftarrow \mathbf{0}$ (Initialization)
2: $\mathbf{v} \leftarrow \mathbf{y}$
3: $k \leftarrow 0$
while halting criterion **do**
4: $k \leftarrow k + 1$
5: $\mathbf{u} \leftarrow \mathbf{\Phi}^* \mathbf{v}$ (Signal proxy)
6: $\Omega \leftarrow \mathbf{supp}\,(\mathbb{W}(\mathbf{u}, 2K))$ (Identification)
7: $\Lambda \leftarrow \Omega \cup \mathbf{supp}\left(\mathbf{a}^{k-1}\right)$ (Support merger)
8: $\mathbf{b}|_\Lambda \leftarrow \mathbf{\Phi}_\Lambda^\dagger \mathbf{u}$ (Estimation)
9: $\mathbf{b}|_{\Lambda^c} \leftarrow \mathbf{0}$
10: $\mathbf{a}^k \leftarrow \mathbb{W}(\mathbf{b}, K)$ (Pruning)
11: $\mathbf{v} \leftarrow \mathbf{y} - \mathbf{\Phi}\mathbf{a}^k$ (Sample update)
until **(while)**

IV. Simulation Results

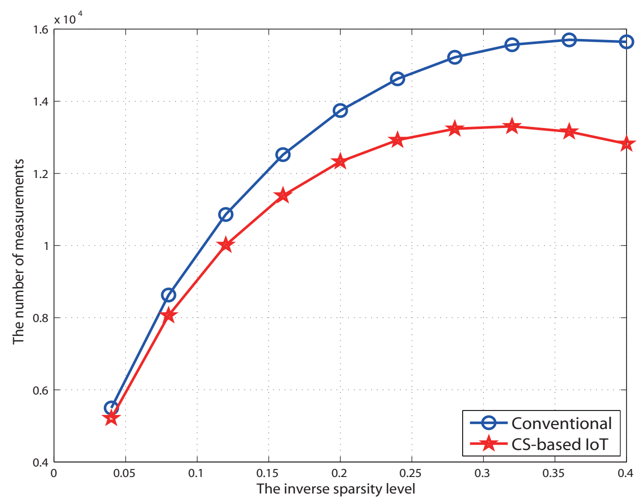

Fig. 2: A difference between the number of measurements with respect to conventional and CS-based IoT methods.

In Fig. 2 the number of measurements as a function of the inverse sparsity level for conventional encoding and CS-based IoT methods is compared. As shown in Fig. 2, the values indicate that the CS-based IoT method introduces a gain in the number of measurements as compared to the conventional encoding method. In other words, while the CS-based method uses the same number of non-zero values as conventional one, it exhibits improved compression efficiency due to a reduction in the number of measurements.

V. Conclusion

CS makes it possible to create standalone and net-centric applications with fewer resources required in Internet of Things (IoT). CS-based signal and information acquisition/compression paradigm combines the nonlinear reconstruction algorithm and random sampling on a sparse basis that provides a promising approach to compress signal and data in information systems. We investigated how CS can provide new insights into coexisting heterogeneous IoT environments. Compression should be performed locally at each Access Point (AP) and reconstruction was executed jointly to consider dependencies in the acquired data by the final fusion center.

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