Sparsest Random Scheduling for Compressive Data Gathering in Wireless Sensor Networks

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***Abstract*—Compressive sensing (CS)-based in-network data processing is a promising approach to reduce packet transmission in wireless sensor networks. Existing CS-based data gathering methods require a large number of sensors involved in each CS measurement gathering, leading to the relatively high data transmission cost. In this paper, we propose a sparsest random scheduling for compressive data gathering scheme, which decreases each measurement transmission cost from $O(N)$ to $O(\log(N))$ without increasing the number of CS measurements as well. In our scheme, we present a sparsest measurement matrix, where each row has only one nonzero entry. To satisfy the restricted isometric property, we propose a design method for representation basis, which is properly generated according to the sparsest measurement matrix and sensory data. With extensive experiments over real sensory data of CitySee, we demonstrate that our scheme can recover the real sensory data accurately. Surprisingly, our scheme outperforms the dense measurement matrix with a discrete cosine transformation basis over 5 dB on data recovery quality. Simulation results also show that our scheme reduces almost 10× energy consumption compared with the dense measurement matrix for CS-based data gathering.**

***Index Terms*—Wireless sensor networks, in-network compression, compressive sensing, restricted isometry property, energy efficiency.**

I. Introduction

WIRELESS SENSOR NETWORKs (WSNs) have been proved to be a powerful tool for long time natural environment monitoring [8], [36]. Many real large-scale systems have been deployed for environment monitoring tasks. For example, GreenOrbs and CitySee systems [12] have been built for natural data collection including temperature, humidity, illumination, and carbon dioxide etc. Unfortunately, extremely large amount of data transmission hinders the applicability and the reliability of the large-scale WSNs deployment. Leveraging the spatial-temporal properties in sensory data from real deployments, in-network compression is an essential technique to reduce the amount of data transmission while preserving relatively high reconstruction accuracy in the sink [2].

Compressive sensing (CS) based in-network data processing is a promising technique to compress sensory data and accurately recover it in the sink. In recent years, many CS based data gathering methods have been proposed to reduce in-network data transmission cost (e.g., [17]–[19], [29], [30], [34]). The transmission cost is decided by two factors, each CS measurement transmission cost and the number of CS measurements. CS measurement transmission cost is mainly decided by measurement matrix. The sparse ratio of the measurement matrix determines the number of sensor nodes to participate in each CS measurement gathering. The more nodes participate in each CS measurement gathering, the higher transmission cost will be generated. However, most of the existing CS based data gathering methods use dense measurement matrix [18], [19], [29] or sparse measurement matrix [17], [30] to compress sensory data, which requires large number of sensors to participate in each CS measurement gathering. It results in the fact of that the data gathering transmission cost is still very high. In fact, if measurement matrix is designed according to the representation basis and sensory data, it can become sparser. Can we make the measurement matrix become the sparsest? At the same time, we can find a sparse representation basis. This sparse representation basis and the sparest measurement matrix can recover sensory data accurately without adding the number of CS measurements. If it can be accomplished, the transmission cost of CS based data gathering can be decreased significantly.

In this paper, we propose a sparsest random scheduling for compressive data gathering in large-scale WSNs. In our scheme, we present a sparsest measurement matrix where each row has only one nonzero entry. To recover sensory data accurately and reduce transmission cost, we propose a design method for representation basis, which is properly generated according to the sparsest measurement matrix and sensory data. The contributions of this paper are three folds.

- We design representation basis based on measurement matrix and sensory data in large-scale WSNs, instead of making measurement matrix satisfy any orthonormal representation basis. According to this design approach, we present the sparsest measurement and each CS measurement transmission cost is decreased from $O(N)$ to

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$O(\log(N))$ in multi-hop tree topology sensor networks, where N is the number of sensors.

- We carry out a theoretical analysis that our representation basis can sparsify our sensory data and satisfy the RIP with the sparest measurement matrix, which guarantees that sensory data can be recovered accurately with a small number of CS measurements.
- Through comprehensive experiments with real sensory data of CitySee, we show our scheme can recover sensory data accurately. Surprisingly, our scheme outperforms the dense measurement matrix with DCT basis over 5 dB on data recovery quality. Simulation results also show our scheme reduces almost $10\times$ energy consumption compared with dense random projections for compressive data gathering scheme.

The rest of this paper is organized as follows. Section II reviews the related works. Section III introduces the basic of CS theory. Section IV gives an overview of our data gathering scheme in CitySee system. In Section V, we present the detail of the measurement matrix and representation basis design. Transmission cost analysis and algorithm implementation of our data gathering scheme are presented in Section VI. Section VII reports our experiment and simulation results. We make a conclusion in Section VIII.

II. Related Work

In this section, we summarize the related work of in-network compression data gathering. There are many conventional in-network data compression techniques such as joint entropy coding (e.g., [10], [23]), transform-based coding (e.g., [1], [9], [27]) and distributed source coding [26]. Joint entropy coding and transform-based coding need large amount of data exchanges among sensor nodes and high computational complexity, which are not suitable for resource-constrained sensor networks. Although distributed source coding can compress sensory data without data exchange, it requires the global correlation structure of sensory data as *a priori*, which is usually difficult to obtain.

The emergence of CS theory has opened up a new research avenue for in-network compression. For example, D. Baron *et al.* [26] proposed distributed CS to compress multi-signal exploiting both intra- and inter-signal correlation structures. In [13], [24], Haupt, J. *et al.* applied CS theory to single-hop data gathering in WSNs to obtain efficient compression for network data. In [18], Luo *et al.* proposed compressive data gathering based on CS theory to reduce data transmission cost in large-scale monitoring sensor networks. In [29], [34], [35], J. Wang *et al.* extended CS based data gathering to dual-layer compressed aggregation and adaptive the number of measurements during the data gathering. These methods exploited *dense measurement matrix* to gather CS measurements, the transmission cost of each CS measurement is $O(N)$ because each row of measurement matrix has $O(N)$ nonzero entries, where N is the number of sensors. To recover k-sparse sensory data, it requires $O(k \cdot \log(N))$ CS measurements. In [20], J. Luo *et al.* proposed that applying CS naively may not bring any improvement for WSN data gathering and proposed a hybrid-CS data gathering scheme. The main reason is that measurement matrix is not sparse enough. In [19], C. Luo *et al.* discovered that $[I, R]$ measurement matrix has also good RIP, I is $M \times M$ identity matrix and R is $M \times (N-M)$ dense random matrix. But each CS measurement matrix transmission cost is still $O(N)$. In [30], W. Wang *et al.* proposed *sparse measurement matrix* can also obtain the salient information of compressible signal, each row of it has $O(\log(N))$ nonzero entries, but it requires $O(k^2 \cdot \log(N))$ CS measurements to recovery k-sparse sensory data. Based on sparse measurement matrix, Lee. S *et al.* [17] proposed low coherence projections for efficient routing, but the proposed routing paths were not the shortest routing paths, which would incur additional transmission cost.

So, the transmission cost of CS based data gathering is related to the sparse ratio of measurement matrix and the required number of CS measurements. In [31], [32], X. Wu *et al.* proposed temporal random sampling in one sensor node to recover the whole temporal signal, but they didn't consider spatial signal in large-scale WSN data gathering and its representation basis is inflexible.

III. Basic of Compressive Sensing

CS is a new compression and sampling paradigm compared with traditional compression and sampling paradigm [3], [5], [11]. CS theory asserts that a relatively small number linear combination of a compressible or sparse signal can contain most of its salient information.

We assume that $\mathbf{s} \in \mathbb{R}^N$ is a k-sparse signal. If a signal is k-sparse, it has only k nonzero components or $(N-k)$ smallest components can be ignored. Thus, the information can be extracted from $\mathbf{s}$ by

$$\mathbf{y} = \Phi \mathbf{s} \tag{1}$$

where Φ is an $M \times N$ measurement matrix, $\mathbf{y} \in \mathbb{R}^M$ is measurement vector and $M \ll N$. To recover the signal $\mathbf{s}$, two problems need to be solved: 1) How to design Φ such that the salient information can be extracted from any k-sparse signal? 2) How to design the reconstruction algorithm to recover $\mathbf{s}$ from M CS measurements $(M \ll N)$? For the first problem, Φ should satisfy the restricted isometric property (RIP) [7]:

Definition 1 (RIP [7]): A matrix Φ satisfies the restricted isometry property of order k if there exists a $\delta_k \in (0,1)$ such that

$$(1-\delta_k)\|\mathbf{s}\|_2^2 \leq \|\Phi \mathbf{s}\|_2^2 \leq (1+\delta_k)\|\mathbf{s}\|_2^2 \tag{2}$$

for all k-sparse vectors $\mathbf{s} \in \mathbb{R}^N$.

Candès, Romberg, and Tao [6] and Donoho [11] have shown many random matrices satisfy the RIP such as Gaussian identity distribution matrix, ± 1 Bernoulli matrix and so on.

For the second problem, the signal $\mathbf{s}$ can be recovered via ℓ_1 optimization as

$$\hat{\mathbf{s}} = \arg\min_{\mathbf{s}} |\mathbf{s}\|_1 \quad s.t. \quad \mathbf{y} = \Phi \mathbf{s} \tag{3}$$

Fig. 1. Partial deployment area of CitySee system.

If Φ satisfies RIP and $M \geq O(k \cdot \log(N/k))$, then $\mathbf{s}$ can be recovered successfully with high probability. If the measurement vector $\mathbf{y}$ contains noise, then the signal $\mathbf{s}$ can be recovered via

$$\hat{\mathbf{s}} = \arg\min_{\mathbf{s}} \|\mathbf{s}\|_1 \quad s.t. \quad \|\Phi\mathbf{s} - \mathbf{y}\|_2^2 \leq \epsilon \tag{4}$$

where ϵ bounds the noise. There already exist many efficient algorithms to solve the above problems such as basis pursuit [7], orthogonal matching pursuit (OMP) algorithm [28], CoSaMP [22] and so on.

However, the real sensory signals are almost compressible signals instead of sparse signal. But a compressible signal can be transformed into a sparse signal via sparse basis transformation. For example, a smooth signal $\mathbf{x} \in \mathbb{R}^N$ can usually be transformed into a sparse signal $\mathbf{s}$ under discrete cosine transformation (DCT) basis or discrete wavelet transformation (DWT) basis. The measurement vector $\mathbf{y}$ can be expressed as

$$\mathbf{y} = \Phi\mathbf{x} = \Phi\Psi\mathbf{s} \tag{5}$$

where Ψ is a $N \times N$ representation basis. If $\Phi\Psi$ satisfies RIP, the sparse signal $\mathbf{s}$ can be recovered accurately with high probability. Then $\mathbf{x}$ can be recovered via $\mathbf{x} = \Psi\mathbf{s}$.

IV. Overview

In this section, we will give the overview of our sensory data gathering scheme. Our scheme is mainly applied to CitySee system data gathering. CitySee was deployed in an urban area of Wuxi City, China, which contained thousands of wireless sensor nodes for monitoring temperature, humidity, light, location, and etc [12], [21]. The partial deployment area is shown in Fig. 1. In CitySee system, each sensor samples once every 10 minutes and sends its sampling value to the sink by multi-hop routing strategy. We will focus on the monitoring of temperature evolution at a single sink area, as the discussion and methodology equally apply to the other monitoring parameters and the whole monitoring area.

Many CS based data gathering techniques were proposed for reducing the network communication cost (e.g., [17]–[19], [35]). These techniques assumed that the sensory data has a good compression performance under the common sparse presentation basis such as DCT, DWT and etc. However, the

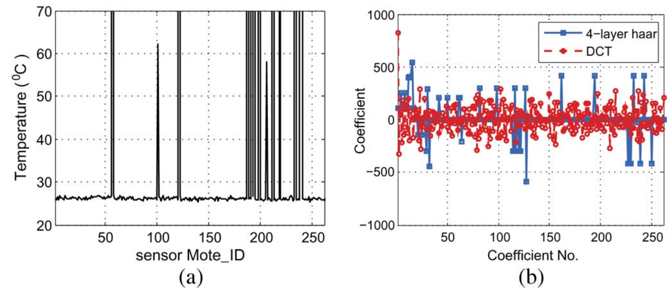


Fig. 2. Original sensory data analysis. (a) The original sensory data. (b) The transformed coefficients.

compression performance of CitySee original sensory data is very poor under these common representation bases. CS is only suitable for sparse or compressible signal, so these bases are not suitable for our sensory data. Fig. 2(a) and (b) display the original sensory data and its transformed signal under DCT basis and 4-layer 'haar' DWT basis. It shows that the transformed signals are not sparse. Simultaneously, Fig. 2(a) also shows that most of the sensory data changes in a small range except for a few sensory values.

In order to reduce network transmission cost and improve the compression of sensory data, a few sensory values that affect compression performance needs to be removed. In our scheme, the sensory data are partitioned into two cases to gather them separately. To facilitate partition different sensory value, we give two thresholds Th_max and Th_min. The sensory data gathering process is carried out as the following two cases:

Case 1: If sensory value is out of the range of (Th_min, Th_max), the sensor node sends it to the sink. This type of sensory values isn't taken compression operation because the proportion of them is relatively small. Even we perform compression operation for them, the network communication cost reduction is also small. Fig. 2(a) shows that the number of them is only 12 among 260 sensory values. This type of sensory values can be considered as sparse signal. However, CS based sparse signal gathering cannot reduce the transmission cost compared with non-compression data gathering [20]. So, this type of sensory data is not appropriate for carrying out CS based data gathering. In our scheme, Th_min and Th_max are set to 10 °C and 50 °C respectively, because most of the time the temperature of CitySee deployment area is between 20 °C to 45 °C, such as from April to October. Our sensory data comes from August. Although the temperature is usually between -5 °C and 20 °C in the winter, the threshold values also can be adjusted to meet environment changed. In addition, Citysee temperature data are mainly used for studying the growth of plants, most plants do not grow in the winter.

Case 2: If sensory value is between Th_min to Th_max, it is carried out CS based data gathering. In fact, the compression performance of sensory data can be improved significantly when the out of the range of (Th_min, Th_max) sensory values are removed. Fig. 3(a) and (b) show the sensory data between Th_min to Th_max and its transformed signals respectively. To simplify the expression, sensory data between Th_min to Th_max are called normal sensory data. According to Fig. 3(b), it displays the transformed signal is very sparse under DCT and DWT basis.

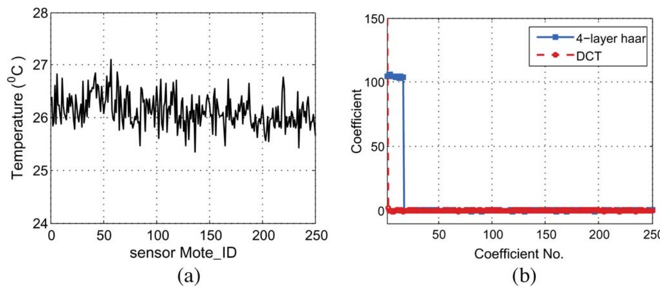


Fig. 3. Normal sensory data analysis. (a) Normal sensory data. (b) The transformed coefficients.

During CS based data gathering, the sparse ratio of measurement matrix determines CS measurement transmission cost. To simplify the expression, we assume that the monitoring area contains N normal sensory values, they are denoted by $\mathbf{x} = [x_1, x_2, \ldots, x_N]^T$, the measurement matrix is denoted by $\Phi = [\phi_1, \phi_2, \ldots, \phi_N]^T$. The ith CS measurement is represented as $y_i = \sum_{j=1}^{N} \phi_{ij} x_j$. If ϕ_{ij} is nonzero, the jth sensor node requires to participate in ith CS measurement gathering. So, the greater number of sensor nodes participates in one CS measurement, the higher transmission cost generates.

Although sparse measurement matrix [30] can reduce single CS measurement transmission cost, it needs to increase the additional number of CS measurements. How to make measurement matrix sparser without increasing the additional number of CS measurements is a big challenge for CS based data gathering. However, CS theory is focused on minimizing the number of CS measurements, rather than on minimizing the cost of each measurement. So, the existing measurement matrix and representation basis of CS theory are hard to meet wireless sensory network requirement.

Whether can we make a measurement matrix extremely sparse where each row has only one nonzero entry? If it can be implemented, each CS measurement transmission cost can be reduced to $O(\log(N))$ in multi-hop tree-type topology sensor network. It is also the minimum transmission cost for single CS measurement when the data packets route along the shortest path. To simplify the expression, we call the measurement matrix with only one nonzero entry in each row as *sparsest measurement matrix*. If we can use sparsest measurement matrix for CS based data gathering without increasing the number of CS measurement as well, we call this method as sparsest random scheduling for compressive data gathering (SRSCDG). In our scheme, we design representation basis based on sparsest measurement matrix and sensory data. Finally, we give the detail implementation data gathering scheme based on sparsest measurement matrix.

V. Design of Our CS Based Data Gathering

According to CS based data gathering, we know sparsest measurement matrix can make CS measurement transmission cost minimal. However, the total transmission cost also relates to the number of CS measurements. If sparsest measurement matrix is used for CS based data gathering without increasing the number of CS measurement as well, the total data gathering transmission cost can be reduced significantly. Thus, we formally define the sparsest measurement matrix Φ_e as

$$\Phi_e(i,j) = \begin{cases} 1 & j = r_i \\ 0 & otherwise \end{cases} \tag{6}$$

where $i = 1, 2, \cdots M$, $j = 1, 2, \cdots N$, r_i represents the independent and identically distributed (i.i.d) random index and $r_i \in [1, N]$. Based on the definition of Φ_e, we know Φ_e is a M by N matrix and each row has only one nonzero entry. If Φ_e is considered as a measurement matrix for CS based data gathering, then one round of data gathering can be expressed as

$$\mathbf{x_r} = \begin{bmatrix} x_{r_1} \\ x_{r_2} \\ \vdots \\ x_{r_M} \end{bmatrix} = \begin{bmatrix} \phi_1^e \\ \phi_2^e \\ \vdots \\ \phi_M^e \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{bmatrix} \tag{7}$$

where ϕ_i^e represents the ith row of Φ_e. The vector $\mathbf{x_r}$ is CS measurement vector and each component of $\mathbf{x_r}$ is randomly selected from $\mathbf{x}$. If we exploit $\mathbf{x_r}$ to recover $\mathbf{x}$ based on CS theory, then the recovery process can be expressed as

$$\hat{\mathbf{s}} = \arg\min_{\mathbf{s}} \|\mathbf{s}\|_1 \quad s.t. \quad \|\Phi_e \Psi \mathbf{s} - \mathbf{x_r}\|_2^2 \le \epsilon \tag{8}$$

and

$$\hat{\mathbf{x}} = \Psi \hat{\mathbf{s}} \tag{9}$$

where $\mathbf{s}$ is the transformed signal under representation basis Ψ, ϵ bounds the mount of recovery error and noise in $\mathbf{x_r}$, $\hat{\mathbf{s}}$ and $\hat{\mathbf{x}}$ are the recovery signals for $\mathbf{s}$ and $\mathbf{x}$ respectively.

Can we make the measurement matrix become the sparsest without increasing the number of its rows? Now, we explain why measurement matrix can be the sparsest from the information extraction aspect. If sensory data $\mathbf{x}$ is sparse under representation basis Ψ, it can be recovered from a small number of CS measurements $\mathbf{y} = \Phi\mathbf{x} = \Phi\Psi\mathbf{s}$. The decoding process is to recover the sparse signal $\mathbf{s}$ instead of directly recovering the sensory data $\mathbf{x}$. The sparse signal $\mathbf{s}$ can be recovered because each component of $\mathbf{y}$ contains a part of information of $\mathbf{s}$, namely, each component of $\mathbf{y}$ is a linear combination of $\mathbf{s}$. However, each component of $\mathbf{x}$ is also a linear combination of $\mathbf{s}$. Components of $\mathbf{x}$ and $\mathbf{y}$ are both the linear combination of $\mathbf{s}$. So, if we design or select a suitable representation basis and make it satisfy RIP with our designed sparsest measurement matrix, the sparse signal $\mathbf{s}$ can be recovered from a part of $\mathbf{x}$.

If Φ_e can be considered as measurement matrix for CS based data gathering, we must find a representation basis Ψ and make it satisfy the following two conditions: 1) Ψ should sparsify our sensory data and 2) $\Phi_e\Psi$ should satisfy RIP. In the next subsection, we give the detail representation basis design.

A. Representation Basis Design

In this subsection, we present a method to establish representation basis based on the sparsest measurement matrix and sensory data. In [6], [11], Donoho *et al.* proposed that the partial Fourier coefficient can also recover original signal.

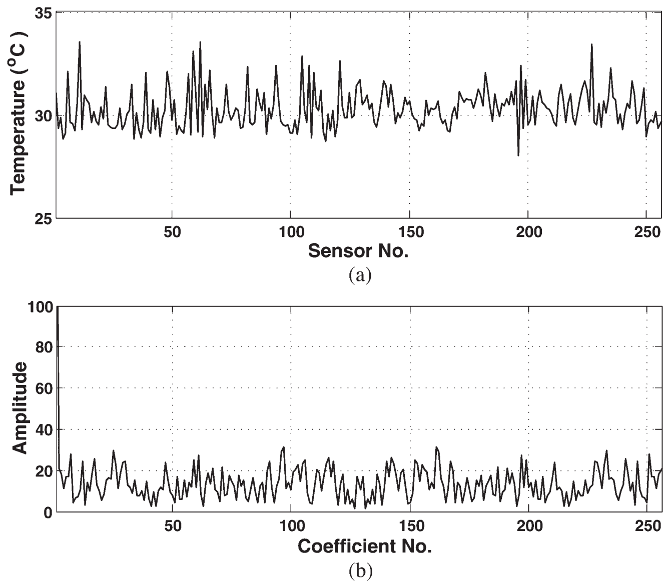


Fig. 4. Sensory data and Fourier transform. (a) The original sensory data. (b) Amplitude values of Fourier transform.

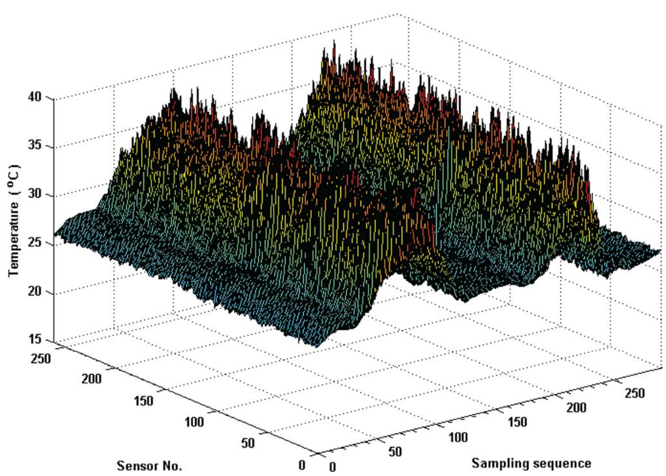


Fig. 5. Temperature sensory data by 260 sensor nodes in two days.

However, the CitySee sensory data cannot be transformed into sparse signal under discrete Fourier representation basis. Fig. 4(a) shows 256 original sensory data at the same sampling time. Fig. 4(b) displays that the transformed coefficients of Fig. 4(a) is not sparse under discrete Fourier transform. So, discrete Fourier transform is not suitable for our monitoring environment. According to the CS theory, the measurement matrix is a random matrix and the RIP is also a probability condition. In other words, if we find a sparsity representation basis which is similar to a certain random matrix, It maybe satisfies RIP condition. Then, we present a representation basis design method based on the correlation of sensory data.

As large-scale WSNs sensory data has strong spatial correlation, it can be obtained via the covariance function. Fig. 5 displays two days temperature sensory data which contain 260 sensor nodes. It illustrates that the sensory data have a strong correlation. To sparsify the sensory data, the covariance matrix is a good tool which can make the sensory data decorrelation and concentrate the sensory data into a few components [16], [25]. We define the covariance matrix as

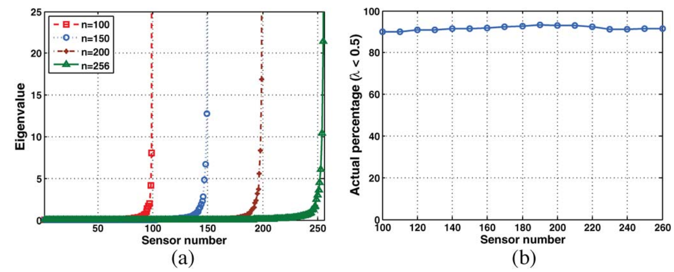


Fig. 6. The eigenvalues of covariance matrix with different number of sensors. (a) Eigenvalue of Σ. (b) Actual percentage of eigenvalue.

$$\Sigma = \mathbb{E}(\mathbf{x}\mathbf{x}^T) \tag{10}$$

Σ is a real symmetric matrix, it can be expressed as

$$\Sigma = U\Lambda U^T \tag{11}$$

where U is orthonormal eigenvector basis, Λ is the diagonal matrix whose diagonal entries are the eigenvalues of Σ. We use $\Psi_G = U$ as our orthonormal representation basis, then $\mathbf{x}$ can be expressed as

$$\mathbf{x} = \Psi_G \mathbf{s}. \tag{12}$$

If $\mathbf{s}$ is sparse and $\Phi_e \Psi_G$ satisfy RIP, Ψ_G can be considered as a representation basis for Φ_e and our sensory data. The proofs of these two conditions are given in the following subsections.

B. *Does* s *Satisfy Sparsity?*

In this subsection, we analyze and prove that Ψ_G can sparsify our sensory data. Firstly, we analyze the eigenvalues of our covariance matrix. In our scheme, we select 289 rounds sensory data to construct the covariance matrix. Fig. 6(a) shows the eigenvalues of covariance matrices with different number of sensors. It illustrates that most of the eigenvalues are almost close to zero. Fig. 6(b) shows that 90% of the eigenvalues are less than 0.5. The analysis results indicate that the eigenvalues are concreted in a few dimensions. Secondly, we prove that $\mathbf{s}$ is sparse according to the analysis results of eigenvalue. We assume $\Psi_G = [\psi_1, \psi_2, \ldots, \psi_N]$ and $\Lambda = \mathrm{diag}\{\lambda_1, \lambda_2, \ldots, \lambda_N\}$. Then, ψ_i is the eigenvector of λ_i because of $\Sigma = \Psi_G \Lambda \Psi_G^{-1}$, $i = 1, 2, \ldots, N$.

In order to prove that $\mathbf{s}$ is sparse under representation basis Ψ_G, we assume that the eigenvalues of covariance matrix are mainly concentrated in d eigenvalues and $\lambda_1 > \lambda_2 > \cdots > \lambda_d > \cdots > \lambda_N$. Then $\sum_{i=d+1}^{N} \lambda_i$ can be considered as a tends to zero. If we use $\hat{\mathbf{s}} = [s_1, s_2, \ldots, s_d, 0, \ldots, 0]^T$ as the estimation of $\mathbf{s} = [s_1, s_2, \ldots, s_N]^T$, then the estimation error can be calculated as

$$\mathbb{E}\left(\|\mathbf{s} - \hat{\mathbf{s}}\|_2^2\right) = \mathbb{E}\left(\sum_{i=d+1}^{N} s_i^2\right) = \mathbb{E}\left(\sum_{i=d+1}^{N} \psi_i^T \mathbf{x}\mathbf{x}^T \psi_i\right)$$

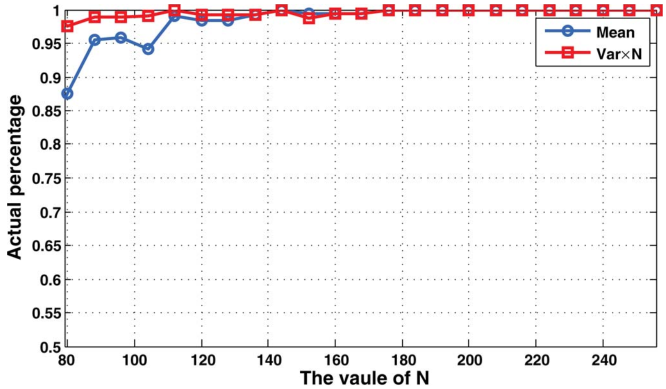


Fig. 7. The mean and variance of every row of Ψ_G.

$$= \sum_{i=d+1}^{N} \left(\psi_i^T \mathbb{E}(\mathbf{x}\mathbf{x}^T)\psi_i\right) = \sum_{i=d+1}^{N} \psi_i^T \Sigma \psi_i$$

$$= \sum_{i=d+1}^{N} \psi_i^T \lambda_i \psi_i = \sum_{i=d+1}^{N} \lambda_i \to 0. \tag{13}$$

The eigenvalues are concentrated in a few elements, d relative N is very much smaller. So, the signal $\mathbf{s}$ can be considered as a sparse signal under representation basis Ψ_G.

C. Does $\Phi_e \Psi_G$ Obey RIP?

In this subsection, we first give the statistic properties of Ψ_G and display that Ψ_G can be considered a random matrix. Mean and variance are two important metrics for data statistics. We calculate mean and variance of each row and column of Φ_e with N from 80 to 300, N is the dimension of Φ_e. Fig. 7 displays that the actual percentage of the mean of each row in the range of (−0.02,0.02) and N times variance of each row in the range of (−0.05,0.05). Fig. 7 illustrates that the mean and variance of each row are both tending to the same with high probability when N is greater than 100. According to the law of large numbers, each row of Ψ_G can be considered as a random sequence generated by a random variable. Ψ_G is generated by N random variables denoted by $\xi_1, \xi_2, \cdots \xi_N$. These random variables have the same numerical characteristics, namely, $\mathbb{E}(\xi_i) = 0$, $\mathrm{Var}(\xi_i) = \mathbb{E}(\xi_i^2) = 1/N$, $(i = 1, 2, \ldots, N)$.

Let $\Theta = \Phi_e \Psi_G$, since the nonzero element of each row of Φ_e is independent of each other, we can assume that each row of Θ is selected independently from Ψ_G. Meanwhile, Θ can be considered as generated by (i.i.d) random variables $\xi_{r_1}, \xi_{r_2}, \ldots, \xi_{r_M}$. In the following, we give the definition of *sub-Gaussian* and the related Corollary.

Definition 2 (Sub-Gaussian [4]): A random variable ξ is called sub-Gaussian if there exists a constant $c > 0$ such that

$$\mathbb{E}(e^{\lambda \xi}) \leq e^{\frac{c^2 \lambda^2}{2}} \tag{14}$$

holds for all $\lambda \in \mathbb{R}$. We use the notation $\xi \sim Sub(c^2)$ to denote that ξ satisfies the above inequality.

Corollary 1 ([33]): If the ith row of Θ is considered as a generated sequence by random variable ξ_{r_i} $(i = 1, 2, \ldots, M)$, then random variable $\xi_{r_i} \sim Sub(2)$.

Theorem 1 ([33]): Fix $\delta \in (0, 1)$ and each row of Θ satisfy $Sub(2)$, if the number $M = O(k \log(N/k))$, then the probability of Θ satisfy

$$(1 - \delta) \leq \frac{\|\Theta \mathbf{v}\|_2^2}{\|\mathbf{v}\|_2^2} \leq (1 + \delta) \tag{15}$$

for all N-dimensional k-sparse signal $\mathbf{v}$, it tends to 1.

According to the Theorem 1, we know that Ψ_G can sparsify our sensory data and satisfy the RIP with Φ_e as well.

VI. Transmission Cost Analysis and Algorithm Implementation

In this section, we first analyze the transmission cost of our scheme, and then give the algorithm implementation of our scheme in detail.

A. Transmission Cost Analysis

In this subsection, we analyze transmission cost of our scheme and compare it with traditional data gathering schemes. We compare our scheme with three conditional data gathering schemes: non-compression data gathering scheme, dense random projections and sparse random projections for CS based data gathering schemes. Consider a sensor network of N sensors with diameter d hops, the average hops of each sensor from the sink is also d. Every sensor node sends its data packet to the sink along the shortest path tree. Due to dense measurement matrix and sparse measurement matrix are suitable for any orthonormal representation basis, we assume that they have the same representation basis. The sensory data is k-sparse under this representation basis. Our scheme uses Ψ_G as representation basis, we assume that the sensory data is k'-sparse. Since Ψ_G is an orthonormal representation basis, it can also be considered as the representation basis for dense and sparse measurement matrix. If Ψ_G is chosen as the representation basis of dense and sparse measurement matrix, then $k = k'$.

For non-compression data gathering scheme, the average transmission cost for each sensory value is $O(d)$, N sensory values need to be sent to the sink. The data collection transmission cost of one round, TC_{non_comp}, is

$$TC_{non\_comp} = O(dN). \tag{16}$$

For dense measurement matrix for CS based data gathering, each row has $O(N)$ nonzero entries such as [18], [19]. Each CS measurement transmission cost is $O(N)$ and the sink needs to gather $O(k \log(N))$ measurements to recovery sensory data. As a result, the transmission cost of one round data gathering, TC_{drp_CS}, is

$$TC_{drp\_CS} = O\left(N \cdot k \log(N)\right) = O\left(kN \log(N)\right). \tag{17}$$

For sparse measurement matrix for CS based data gathering such as [17], [30], the number of nonzero entries of each row is $O(\log(N))$ and $O(k^2 \log(N))$ measurements are required to recover sensory data. But each nonzero entry is random, each

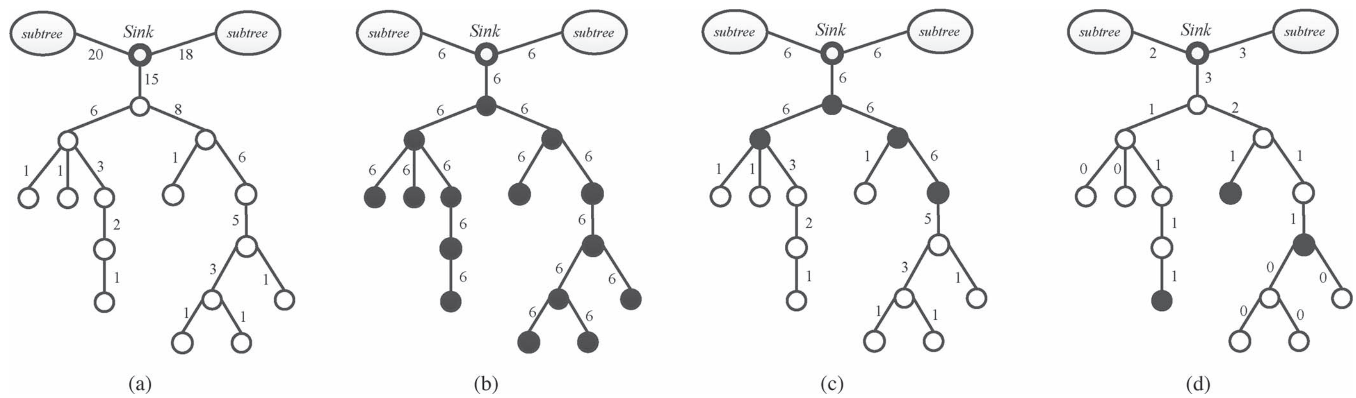


Fig. 8. Communication cost comparison under multi-hop tree-type topology. (a) Non-compression. (b) Dense measurement matrix. (c) Hybrid CS. (d) Sparsest random scheduling.

CS measurement transmission cost is $O(d\log(N))$. A round data gathering transmission cost, TC_{srp_CS}, is

$$\begin{aligned} TC_{srp\_CS} &= O\left(d\log(N)\cdot k^2\log(N)\right) \\ &= O\left(dk^2\log^2(N)\right). \end{aligned} \quad (18)$$

In our scheme, each measurement has only one nonzero entry, the transmission cost of one CS measurement is $O(d)$. Our scheme requires $O(k'\log(N))$ measurements to recover sensory data. As a result, the transmission cost of one round data gathering, TC_{our}, is

$$TC_{our} = O\left(d\cdot k'\log(N)\right) = O\left(dk'\log(N)\right). \quad (19)$$

According to the above analyses, we can obtain the following two results. (1) $TC_{non\_comp} = O(dN) < TC_{drp\_CS} = O(kN\log(N)$ if $d < k\log(N)$. (2) Our scheme has the least transmission cost if $k' < k^2\log(N)$. Consider the real routing topology of sensor networks usually adopts multi-hop tree-type topology, the height of N-sensor routing tree is $O(\log(N))$. So, dense measurement matrix for CS based data gathering is hard to reduce data transmission cost. Our proposed representation basis Ψ_G has a good compression function for sensory data, k' is not greater than $k^2\log(N)$. In [20], J. Luo *et al.* has also shown that applying CS naively may not bring any performance improvement and proposed a hybrid-CS data gathering scheme. In hybrid-CS data gathering scheme, if the number of transmission data packets is larger than CS measurements, the sensor carries out dense random projections. Otherwise, the sensor takes non-compression operation which only relays data packets. Fig. 8 shows four types of data gathering: non-compression data gathering, dense measurement matrix for CS based data gathering, hybrid-CS data gathering and sparsest random scheduling for CS data gathering. In Fig. 8, the black sensors represent the participation compression sensor nodes during CS based data gathering and the link labels represent the number of transmission data packets during a round data gathering. Fig. 8 illustrates that our scheme significantly outperforms than the other three types of data gathering schemes.

B. Algorithm Implementation

To implement the sparsest random scheduling for compressive data gathering scheme, two aspects need to be considered: (1) How to select M random scheduling sensors from N deployment sensors to meet Φ_e while keeping each sensor participates evenly. (2) How to adaptively assign the number of CS measurement based on recovery error. For the first aspect, we develop a probabilistic scheduling strategy which can satisfy the proposed measurement matrix and ensure balanced sensor participation. For the second aspect, we can use recovery error of received sensory data to adjust scheduling probability. In the following part, we implement our sparsest random scheduling for data gathering scheme, which contains two components. The sink is responsible for sensory data recovery and random scheduling probability assignment as shown in Algorithm 1. Each sensor is responsible for sampling and transmitting its sampling value to the sink shown in Algorithm 2.

Algorithm 1: Sensory data recovery and scheduling probability assignment/adjustment.

Input : received sensory data $\mathbf{x_r}$, representation basis Ψ_G, recovery error upper bound ϵ_{ub} and lower bound ϵ_{lb}, probability step length $\triangle p$.
Output: recovery sensory data $\hat{\mathbf{x}}$, sensor scheduling probability p_s;

$\Phi_e \leftarrow \mathbf{0}$; /* *Initializing measurement matrix* */
$\Omega_\mathbf{r} \leftarrow \{i|$ if x_i received $\}$; /* *Record the index of received sensory data* */
$j \leftarrow 1$;
foreach $i \in \Omega_\mathbf{r}$ **do**
  $\Phi_e(j,i) \leftarrow 1$; /* *Assign measurement matrix* */
  $j \leftarrow j+1$;
$\Theta \leftarrow \Phi_e * \Psi_G$;
$\hat{\mathbf{u}} = CS\_Recovery(\Theta, \hat{x}_r)$; /* *Recovery sparse signal* */
$\hat{\mathbf{x}} = \Psi^{-1}\hat{\mathbf{u}}$; /* *Recovery the entire sensory data* */
$\hat{\mathbf{x}}_\mathbf{r} \leftarrow \hat{\mathbf{x}}_{\Omega_\mathbf{r}}$; /* *Extract received recovery sensory data* */
$\epsilon = \frac{\|\mathbf{x_r}-\hat{\mathbf{x}}_\mathbf{r}\|_2}{\|\mathbf{x_r}\|_2}$; /* *Recovery error of received sensory data* */
$p_s \leftarrow |\Omega_\mathbf{r}|/N$; /* *Current scheduling probability* */
if $\epsilon > \epsilon_{ub}$ **then**
  $p_s \leftarrow p_s + \triangle p$; /* *Increase scheduling probability* */
  $broadcast\ p_s\ to\ all\ sensors$;
else if $\epsilon < \epsilon_{lb}$ **then**
  $p_s \leftarrow p_s - \triangle p$; /* *Decrease scheduling probability* */
  Broadcast p_s to all sensors;
return $\hat{\mathbf{x}}$, p_s;

Algorithm 2: Random scheduling data gathering for the i^{th} sensor.

```
Input  : Random scheduling probability p_s
Output : Sensory value x_i
if x_i ∈ (Th_min, Th_max) then
    p_r ← rand(); /* Generate a random probability ∈ (0, 1) */
    if p_r ≥ p_s then
        Send_data(x_i,'NORMAL');
else
    Send_data(x_i,'ABNORMAL');
```

In Algorithm 1, the inputs are the received sensory data $\mathbf{x_r}$, representation basis Ψ_G, the error upper bound ϵ_{ub} and lower bound ϵ_{lb}, the scheduling probability step length Δp. In the initializing data gathering stage, the sensor scheduling probability can be set to 1. The outputs are the recovery sensory data $\hat{\mathbf{x}}$ and sensor scheduling probability p_s. During the data gathering, the indices of received sensory data need to be recorded in $\Omega_\mathbf{r}$ which is used for generating Φ_e. ϵ is the recovery error of received sensory data. If recovery error ϵ is greater than ϵ_{ub} which means the number of CS measurements is not enough to recover the sensory data, the number of CS measurements needs to increase. If ϵ is less than ϵ_{lb}, we need to decrease the number of CS measurements to save the resource consumption. The scheduling probability p_s needs to be assigned to each sensor when the recovery error is out of the range of $(\epsilon_{lb}, \epsilon_{ub})$. The scheduling probability will not change frequently because the sensory data correlation is stable at most time. $\hat{\mathbf{u}}$, $\hat{\mathbf{x}}$, and $\hat{\mathbf{x}}_\mathbf{r}$ represent the recovery signals of $\mathbf{u}$, $\mathbf{x}$, and $\mathbf{x_r}$ respectively.

In Algorithm 2, each sensor periodically obtains a sampling value and judges whether it participates in CS based data gathering or not. If the sensory value is out of the range (Th_min, Th_max), then the sensor sends it to the sink along the shortest routing path. Otherwise, the sensor will generate a random value $p_r \in (0, 1)$. If the random value is smaller than its scheduling probability, the sensor will send its value to the sink along the shortest routing path. Otherwise, the sensor will not send its value.

VII. Experimental Results

In this section, we carry out extensive experiments to evaluate the performance of our scheme. In our experiments, the data set comes from CitySee [12] system which contains more than one thousand sensor nodes, partial deployment area of CitySee system is shown in Fig. 1. Each node in our system samples once every 10 minutes, including temperature, humidity, and other relevant information. We select many snapshots of real temperature sensory data to evaluate our scheme. The evaluation process includes three aspects: the sparsity comparison, the recovery quality of sensory data and energy consumption of sensor network's data gathering. Before the experiments, we give some notations throughout the experiment section as shown in Table I.

A. The Sparsity Comparison

According to CS theory, the number of CS measurement is proportional to the sparse level of recovery sensory data. In our experiments, we compare the sparse level of the same sensory data under Ψ_G and three other representation bases, Ψ_{dct}, 4-layer "haar" Ψ_{dwt} and Ψ_{dft}.

TABLE I
Notations

Notation	Description
Φ_G	Dense random Gaussian matrix
Φ_e	Sparsest measurement matrix
Ψ_G	Our designed representation basis
Ψ_{dct}	Discrete cosine transformation basis
Ψ_{dwt}	Discrete wavelet transformation basis
Ψ_{dft}	Discrete fourier transformation basis

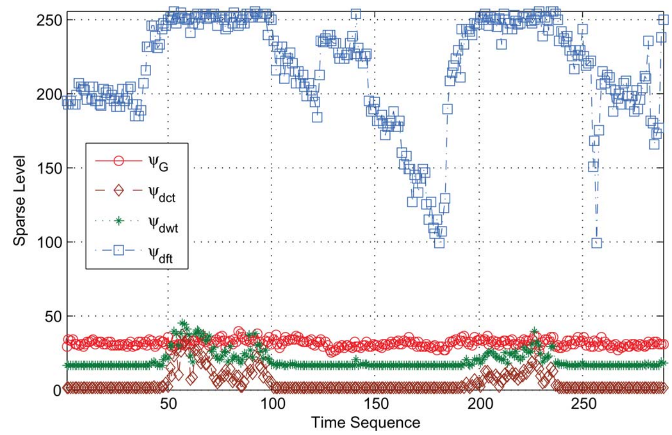


Fig. 9. Sparse level comparison with different representation bases.

In Fig. 9, we displays the sparse level of the same sensory data under Ψ_G, Ψ_{dct}, Ψ_{dwt}, and Ψ_{dft}. The experimental sensory data are 256 sensor nodes with 280 rounds sampling. According to Fig. 9, it illustrates that Ψ_{dft} cannot transform sensory data into sparse signal completely. Ψ_{dct}, Ψ_{dwt}, and Ψ_G all can sparsify our sensory data. Fig. 9 also displays that our designed representation basis Ψ_G can sparsify our sensory data. The compression performance of Ψ_G is only slightly less than Ψ_{dct} and Ψ_{dwt} for our sensory data.

B. CitySee Sensory Data Recovery

In this part of experiments, we adopt OMP [28] as CS recovery algorithm. Although there exits many measurement matrices and the most representation bases satisfy the RIP, Gaussian random matrix is the most common measurement matrix. Ψ_{dct} has the best compression performance compared with 4-layer 'haar' Ψ_{dwt} and Ψ_{dft}. In our experiment, we choose Gaussian random matrix Φ_G and Ψ_{dct} as our comparison measurement matrix and representation basis respectively.

To evaluate the real sensory data recovery performance of our proposed Φ_e and Ψ_G, we carry out the experiments from the following three aspects:

1) Evaluate the sensory data recovery performance using Φ_e and Ψ_G as measurement matrix and representation basis respectively.
2) Compare the recovery performance using (Φ_e, Ψ_G) and (Φ_G, Ψ_{dct}) respectively.
3) Given Φ_e, compare the recovery performance using Ψ_{dct} and Ψ_G as representation basis respectively.

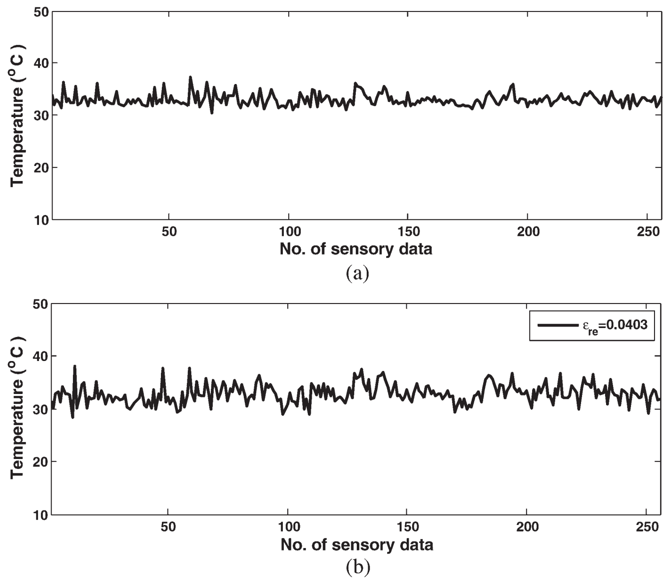


Fig. 10. Original sensory data and recovery sensory data comparison. (a) The original sensory data. (b) Recovery sensory data with 160 CS measurements.

In our scheme, the recovery error of sensory data is calculated as

$$\epsilon_{re} = \frac{\|\mathbf{x} - \hat{\mathbf{x}}\|_2}{\|\mathbf{x}\|_2}. \tag{20}$$

In order to evaluate the sensory data recovery performance more reasonably, we also adopt the peak signal-to-noise ratio (PSNR) as another type of performance metric which is defined as

$$PSNR = 10 \cdot \log_{10}\left(\frac{MaxVal^2}{MSE}\right) \tag{21}$$

where MSE is the mean squared error and $MaxVal$ is equal to 100 in our experiment. We select 256 normal readings from the CitySee system as experimental data which is shown in Fig. 10(a). Fig. 10(b) shows the recovery sensory data using Φ_e and Ψ_G as measurement matrix and representation basis respectively with 160 CS measurements. It displays that 160 CS measurements can recover the sensory data relative accuracy with $\epsilon_{re} = 0.0403$. Fig. 11 displays recovery error comparisons with (Φ_e, Ψ_G) and (Φ_G, Ψ_{dct}). Fig. 11 illustrates that the recovery performance of (Φ_e, Ψ_G) outperforms than (Φ_G, Ψ_{dct}) both on ϵ_{re} and PSNR. According to the RIP and sparsity, the recovery performance of (Φ_e, Ψ_G) and (Φ_G, Ψ_{dct}) should be relatively close. But our experimental results shown that the gap between them almost 5 dB when the number of CS measurements is greater than 100. CS decoding is the fact that selection k largest coefficients as the recovery sparse signal, which may lead to two cases: (1) the recovery error is large being lack of CS measurements or (2) the recovery error is little but the recovery result unsuccessful because the recovery signal is very different from the original signal. But if we have reliable sensory data as the validation data, we can avoid the case (2) to a large extent. It also illustrates that our scheme can reduce the recovery error because the decoder has the reliable validation sensory data.

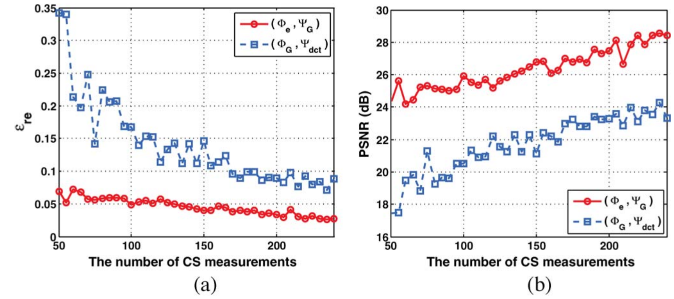


Fig. 11. The recovery performance comparison using (Φ_e, Ψ_G) and (Φ_G, Ψ_{dct}). (a) ϵ_{re} comparison. (b) PSNR comparison.

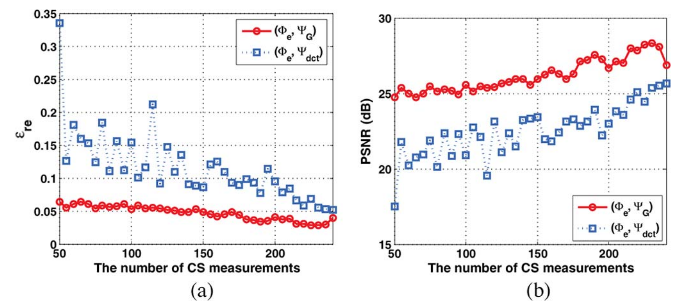


Fig. 12. The recovery performance comparison with (Φ_e, Ψ_G) and (Φ_e, Ψ_{dct}). (a) ϵ_{re} comparison. (b) PSNR comparison.

Fig. 12 shows that the recovery performance comparison using Φ_e as measurement matrix under representation basis Ψ_G and Ψ_{dct}. It illustrates that the recovery performance of Ψ_G is better than Ψ_{dct} with the same measurement matrix Φ_e. The reason is that the production of Φ_e and Ψ_{dct} does not satisfy the RIP of CS theory. According to our experimental results, it indicates that the general representation basis cannot satisfy the CS requirement with Φ_e. Ψ_G can sparsify spatial sensory data and satisfy RIP with Φ_e, which guarantees sensory data can be recovered with high probability.

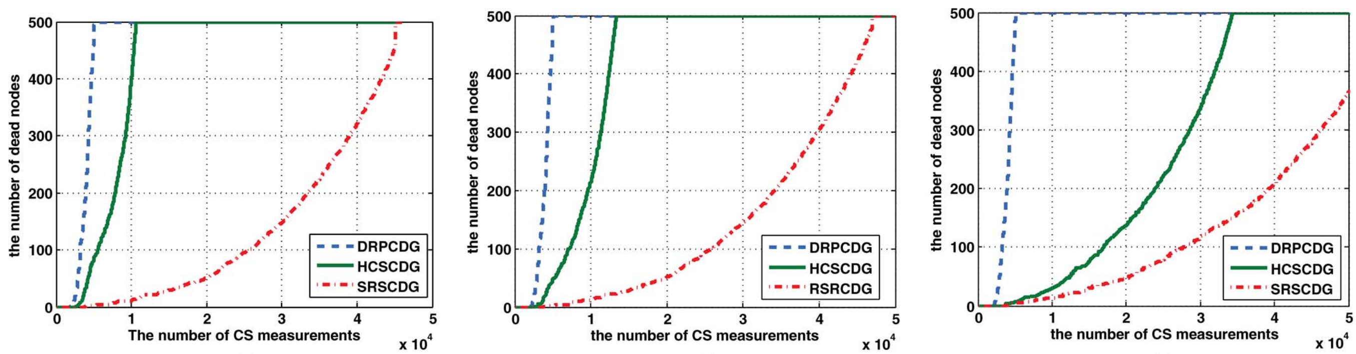
C. Energy Evaluation

To evaluate data transmission cost of our proposed scheme, we use energy consumption as a metric implementation in simulation platform OMNeT++ [15]. In our simulations, we consider a WSN with 500 sensors and a sink deployed in a 1000 m × 1000 m two-dimensional plane. The sink is located at (0,0) and sensors are uniformly distributed in the monitoring area. We use bit-hop metric as the energy consumption model [14] as:

$$E_{Tx}(l,d) = E_{elec} \times l + \epsilon_{amp} \times l \times d^2 \tag{22}$$

$$E_{Rx}(l) = E_{elec} \times l \tag{23}$$

where $E_{Tx}(l,d)$ represents the energy consumption for transmitting a l-bit message over distance d, $E_{Rx}(l)$ represents the energy consumption for receiving a l-bit message, where E_{elec} is the energy consumption for transmitting or receiving one bit message, and ϵ_{amp} is the transmission amplifier. In the simulation, we set $E_{elec} = 50$ nJ/bit, $\epsilon_{amp} = 100$ pJ/bit/m^2, the length of data packet is 1024 bits, each sensor has 5000 J energy.



(a) (b) (c)

Fig. 13. Energy consumption comparison. (a) $\rho = 0.05$. (b) $\rho = 0.1$. (c) $\rho = 0.5$.

To simplify our simulation, we ignore the energy consumption of sampling and data processing, which are relatively smaller compared with data transmission [2].

Although the energy consumption model is somewhat ideal, we only use it to evaluate the transmission cost for data gathering. The bit-hop metric is a favorable metric for such evaluation. Additionally, all the data gathering schemes implement on the same energy consumption model, it does not affect our simulation results. To evaluate the performance of our sparsest random scheduling for compressive data gathering (SRSCDG), we compare it with two traditional CS based data gathering schemes: dense measurement matrix for CS based data gathering (DRPCDG) [18] and hybrid-CS for compressive data gathering (HCSCDG) [20]. The shortest distance square spanning tree is used as the routing strategy. We do not consider sparse measurement matrix ([17], [30]) because it requires larger number of CS measurements to recover sensory data. We also assume ρ is the ratio of the number CS measurements and the number of all sensors ($\rho = M/N$). Since M is proportional to the sparsity of sensory data, ρ also can be considered as the compressibility of gathering sensory data. Fig. 13 shows the comparison results under DRPCDG, HCSCDG and SRSCDG with $\rho = 0.05,\ 0.1,\ 0.5$, respectively. According to Fig. 13, it displays that energy consumption of DRPCDG is the worst. Also, the consumption of HCSCDG and SRSCDG are better than DRPCDG. The energy consumption of our proposed SRSCDG significantly outperforms DRPCDG and HCSCDG. The curves of DRPCDG and HCSCDG is close when the value ρ is small. However the curves of HCSCDG and SRSCDG is also close when the value of ρ is large. Actually, the value of ρ expresses the compressibility of sensory data. If the number of CS measurements to recover sensory data is small, it means the number of non-compression sensors is also small in HCSCDG which leads to the curves of DRPCDG and HCSCDG close. If the number of CS measurements for sensory data recovery is large, it means DRPCDG cannot reduce transmission cost compared with non-compression data gathering. Also, the overall performances of HCSCDG and SRSCDG are close to non-compression data gathering scheme. It also illustrates that any CS data gathering schemes cannot reduce the data transmission cost when the compression performance of gathering sensory data is poor. The simulation result shows that the number of CS measurement of SRSCDG is nearly 10 times of DRPCDG.

VIII. Conclusion and Future Work

In this paper, we investigated compressive sensing based data gathering in large-scale wireless sensor networks. The traditional CS based data gathering methods design measurement matrix based on representation basis, which leads to large of number of sensors involved in each CS measurement gathering. In our scheme, we designed representation basis based on measurement matrix and sensory data. According to this design approach, measurement matrix can be designed according to the requirement of sensor network, rather than match measurement matrix into network environment passively. Experiment results shown our scheme can recover the sensory data accurately. Simulation results also shown our scheme can significantly save energy consumption compared with existing compressive sensing data gathering methods.

Future work will include the following directions. First, different sensory data can have different spatial correlation. It is an interesting and important problem to find adaptively parameter representation basis design. Second, the current work only considered spatial sensory data. The scheme can be further extended to spatial-temporal sensory data.

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