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Global Correlated Data Gathering in Wireless Sensor Networks with Compressive Sensing and Randomized Gossiping

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***Abstract*—In this paper, we address the problem of access to global information from any single point in wireless sensor networks. To this end, we propose a distributed in-network data acquisition approach, on the basis of compressive sensing, in which sparse random projections and randomized gossiping are jointly designed. In the context of unreliable distributed wireless settings, a simple random gossip algorithm is adopted. It allows the sensor to forward the linear combined data (readings) to randomly chosen neighbors. Also, each transmission path of the combined data is mapped to one row of the projection matrix, forming low-cost sparse random projections. Moreover, a theoretical model is developed that exactly characterizes the relationship of the number of sparse projections, the degree of the sparsity, and the error probability. Finally, simulation results show that, compared with the conventional approach, the proposed algorithm can achieve better reconstruction quality with less communication overhead.**

***Index Terms*—Compressive sensing, wireless sensor networks, correlated data gathering, sparse random projections, randomized gossiping**

I. INTRODUCTION

Wireless sensor networks (WSNs) consist of spatially distributed autonomous sensors to monitor physical or environmental conditions such as temperature, pressure, or seismic activity [1]. In view of energy constraints of sensor nodes, in-network data compression is extensively employed for energy-efficient sensor data gathering. It fully exploits local correlations in the data from neighboring sensors so as to avoid processing and transmitting redundant information. However, existing data compression techniques, either requiring the global knowledge of correlation structure (e.g. distributed source coding [2]), or introducing significant computation overhead (e.g. transform coding [3]), would be undesirable for large-scale sensor networks.

Compressive sensing (CS) [4], [5], a novel sensing/sampling paradigm, appears to be a promising alternative in this context. On one hand, it directly acquires projections or measurements of a compressible signal, avoiding inefficient sample-then-compress process. On the other hand, its measurement process is very simple, thus well-suited for resource-constrained sensor nodes. Luo et al. [6] considered large and dense wireless sensor networks, and presented the first complete design on compressive sensing based network data acquisition. The works in [7] and [8] also dealt with data gathering issues in WSNs. They present joint design on routing paths and projection matrix for better reconstruction quality and efficient energy consumption as well.

The data gathering approaches in the foregoing literature are particularly designed for traditional data collection, i.e., converging all the data to a remote fusion center or a sink through a tree communication structure. Such centralized methods generally require complex routing algorithm as well as complicated communication protocol to combat unreliable networking conditions. It inevitably leads to significant overall communication cost. Further, in some specific applications, e.g. network diagnostics, the repairman servicing the network would prefer to be notified of malfunctioning sensors at an arbitrary location within the network, rather than having to return to a fusion center [9].

To cope with the problems previously mentioned, the authors in [9] presented a CS data compression and predistribution scheme that stores and disseminates random projections of sensor data in a distributed manner. In this way, one can extract all the data by querying a small subset of sensors anywhere in the network. However, either spanning tree or Hamilton cycle routing structure necessitates for the projections predistribution. Wang et al. [10] proposed a distributed algorithm based on sparse random projections for sensor data measuring, and proved that sparse random projections can produce an approximation with error comparable to that of conventional compressive sensing. However, how to distribute random projections was not considered. In addition, sparse information dissemination using compressive sensing and random walk has been applied in overlay networks [12], which helps each peer locally access to the information of the entire network.

In this paper, we focus on a decentralized data dissemination and gathering method of low computation and communication overhead, with which the global information of WSNs can be easily obtained at any single sensor. Our main contributions

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are twofold. First, we propose a compressive sensing based in-network data acquisition approach, which makes a joint design of sparse random projections and randomized gossiping. In face of unreliable distributed wireless settings, a simple random gossip algorithm is adopted. It allows the sensor to forward the linear combined data (readings) simultaneously to a set of randomly chosen neighbors without any central coordination. Also, each transmission path of the combined data is mapped to one row of the projection matrix, forming sparse random projections to reduce the communication cost. Second, a theoretical model is developed that exactly characterizes the relationship of the number of sparse projections, the degree of the sparsity, and the error probability. This model provides a practical guideline on choosing key parameters when the proposed scheme is applied in a real system.

The remainder of the paper is organized as follows. Section II provides the background knowledge of compressive sensing. In Section III, we present the network model, and our methodology for correlated data dissemination and collection in WSNs. Section IV develops a bound describing the relationship of reconstruction error with two key parameters of the proposed scheme. Simulation results are shown in Section V. Finally, the paper concludes in Section VI.

II. Compressive Sensing Background

Consider a real-valued signal $\mathbf{x} \in \mathbb{R}^N$ and a certain orthonormal transform basis $\Psi = \{\psi_1, ..., \psi_N\}$. Assume that the signal $\mathbf{x}$ can be sparsely represented over the basis Ψ. That is, $\mathbf{x}$ can be described as $\mathbf{x} = \Psi\theta$, where the transform coefficient vector θ is an $N \times 1$ column vector with K nonzero elements. In this way, the signal $\mathbf{x}$ is viewed as a K-sparse signal. The compressive sensing theory states that it is possible to reconstruct $\mathbf{x}$ from measurements

$$\mathbf{y} = \Phi\mathbf{x} = \Phi\Psi\theta \tag{1}$$

where Φ is an $M \times N$ measurement matrix with $M \ll N$, $\mathbf{y}$ is an $M \times 1$ vector representing the random linear projections of the signal onto the measurement matrix Φ.

Since $M \ll N$, recovery of the original signal $\mathbf{x}$ from the measurement $\mathbf{y}$ is generally ill-conditioned, however, the additional assumption that $\mathbf{x}$ is K-sparse guarantees recovery possible and practical. In particular, recovery of $\mathbf{x}$ can be achieved by exploring the sparse expression of $\mathbf{x}$, i.e., seeking the sparsest coefficient vector among all possible $\hat{\theta}$ that satisfies $\mathbf{y} = \Phi\Psi\theta$. Theoretically, this reconstruction requires the solution to the ℓ_0-norm minimizaiton

$$\hat{\theta} = \arg\ \min \|\theta\|_{l_0}\ , \quad \text{s.t.} \quad \mathbf{y} = \Phi\Psi\theta \tag{2}$$

III. Model and Methodology

In this section, we illustrate a global information gathering scheme for WSNs. By combining sparse random projections and gossip algorithm based on compressive sensing, the proposed scheme allows the querying user to gather all the sensor readings from visiting one sensor anywhere in the network.

A. Network Model and Assumptions

Consider a wireless sensor network consisting of N sensor nodes. Assume that each sensor i has a real-valued scalar measurement x_i, $i \in \{1, 2, ..., N\}$, and all the indexed measurements are represented by a vector $\mathbf{x} \in \mathbb{R}^N$.

Since data collected at nearby sensors is expected to be correlated, we suppose that $\mathbf{x}$ is compressible in an orthonormal basis $\Psi = \{\psi_1, ..., \psi_N\}$. Note that when monitoring the status of the sensor nodes, a normal scenario is that most sensors are functioning well, while a small number are abnormal and need to be replaced. Therefore, there would be $K(K \ll N)$ corrupted sensors with $x_i = 1$, and $N - K$ functioning sensors with $x_i = 0$. In this case, $\mathbf{x}$ itself is sparse (K-sparse) and orthonormal transform is not required. Also, let ϕ_i, $i \in \{1, 2, ..., M\}$ represent a projection vector, and $\Phi = \{\phi_1^T, \phi_2^T, ..., \phi_M^T\}^T$ be the projection matrix.

B. Joint Sparse Random Projections and Randomized Gossiping

To acquire the global signal $\mathbf{x}$ at any single point in the network, each sensor requires to collect all the sensor readings. Consider signal $\mathbf{x}$ is expected to be compressible, the sensor may gather all the readings with high accuracy through collecting a small number of random combinations of the element of $\mathbf{x}$ by compressive sensing. In general, most projection matrices Φ used in the literature are dense matrices (e.g. random ± 1 Bernoulli or Gaussian matrix). This implies that, to complete one projection, nearly all the sensors in the network need to be visited, and this communication cost scales up with the number of sensors. Inspired by studies on sparse random projections [13], [10], we attempt to construct sparse random projections in which a distributed gossip algorithm is incorporated.

Gossip algorithm [11], with simple communication protocol, low computational complexity and strong resilience to network changes, is very suitable for distributed and unreliable WSNs. In our scheme, each sensor will act as a source node in due order to start disseminating random projection of its own reading. Specifically, when sensor i becomes the source node, it firstly generates a data packet containing a random combination value y_i of its own reading x_i, i.e., $y_i = \phi_{h,i} x_i$. Here $\phi_{h,i}$ is a random combination coefficient, or i-th, $i \in \{1, 2, ..., N\}$ entry of h-th CS projection vector ϕ_h, $h \in \{1, 2, ..., M\}$. In accordance with CS theory, each coefficient $\phi_{h,i}$ can be randomly chosen using a pre-defined probability distribution. To simplify the question, we set all $\phi_{h,i} = 1$ when calculating the combination value y_i. Thereafter, sensor i forwards this packet simultaneously to a set λ of randomly chosen neighbors on the basis of gossip algorithm.

Assume that each data packet has a limited lifetime T, i.e., a data packet is allowed to be forwarded for at most T hops. Therefore, when sending the packet out to its neighbors, sensor i must append the residual number of allowed hops (represented by t) and its own ID number to the packet. Note that the former is used for recording the number of transmissions a packet has experienced, while the latter is for constructing the sparse projection matrix. Each time the

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packet is forwarded, its residual hops t is decreased by one unit. When a sensor receives a data packet, it first checks whether the residual hops of the received packet is reduced to zero. If $t \neq 0$, the sensor performs four operations: updates the accumulated combination value y_i in terms of $y_i = y_i + \phi_{h,i} x_i$, replaces t with $t-1$, adds its ID number, and transmits the updated packet to its λ neighbors. On the contrary, if $t = 0$, i.e., the lifetime of the packet comes to an end, the packet would not be forwarded anymore.

When sensor j receives a packet originated from sensor i satisfying $t = 0$, it extracts the accumulated combination value y_i as well as all the ID numbers, and adds a new row ϕ_i in its projection matrix Φ. Clearly, row ϕ_i represents a routing path of a data packet starting from sensor i. If this packet traverses sensor h (i.e., the ID number of sensor h appears in the packet), the h-th entry $\phi_{h,i}$ of ϕ_i is set to 1, else it is zero. Thus, there would be T nonzero entries (i.e. "1" elements) in each ϕ_i, whose positions correspond to the sensors visited by the packet.

It can be easily proved that each sensor would averagely receive λ^T data packets when the proposed algorithm is executed one time. Using λ^T packets, the sensor can construct $M = \lambda^T$ projections of signal $\mathbf{x}$. To accurately recover $\mathbf{x}$ from these projections with high probability, the number M of projections required should be lower-bounded which is detailed in the next section.

IV. Sparse random projections

Our design appears to be a sparse random projections approach as the random routing on the basis of gossip algorithm is used for constructing projection matrix. For sparse random projections, one critical issue is how to choose an appropriate degree of sparsity, namely, the average number of nonzeros in each random projection vector. Moreover, there is an intrinsic trade-off between the sparsity of the random projections and the number of random projections required. How to balance their paradoxical relation should also be taken into account in the proposed approach.

We construct the sparse projection matrix $\Phi \in \mathbb{R}^{M \times N}$ containing entries:

$$\Phi_{i,j} = \begin{cases} +1 & \text{with prob. } \frac{T+1}{N} \\ 0 & \text{with prob. } 1 - \frac{T+1}{N} \end{cases} \quad (3)$$

Note that in the proposed scheme, the degree of sparsity is determined by the maximum lifetime T. The larger the value of T, the less sparsity in the projection matrix. One extreme case is to set $T = N-1$, then all the sensors in the network would be sampled in each projection process. Correspondingly, the projection matrix has no sparsity.

Lemma 1: Suppose that a random matrix $\Phi \in \mathbb{R}^{M \times N}$ with entries $\phi_{i,j}$ satisfying the following conditions [13]:

$$E(\phi_{i,j}) = E(\phi_{i,j}^2) = E(\phi_{i,j}^4) = \frac{T+1}{N} \triangleq a \quad (4)$$

For any two vector $\mathbf{u}, \mathbf{v} \in \mathbb{R}^N$, let $\mathbf{x} = \frac{1}{\sqrt{M}}\Phi\mathbf{u}$, $\mathbf{y} = \frac{1}{\sqrt{M}}\Phi\mathbf{v} \in \mathbb{R}^M$ represent their random projections.

$$Var(\mathbf{x}^T\mathbf{y}) = \frac{a^4}{M}\left((\mathbf{u}^T\mathbf{v})^2 + \|\mathbf{u}\|_2^2\|\mathbf{v}\|_2^2 - 2\sum_{j=1}^N u_j^2 v_j^2\right) \quad (5)$$

Proof: Following the similar analysis in [10], let $\phi_{i,j}$ meet the requirements specified in Eq. (5), then define the random variables

$$\delta_i = \left(\sum_{j=1}^N u_j \phi_{ij}\right)\left(\sum_{j=1}^N v_j \phi_{ij}\right) \quad (6)$$

and the random variable $g = \mathbf{x}^T\mathbf{y} = \frac{1}{M}\sum_{i=1}^M \delta_i$.

$$\begin{aligned} E[\delta_i] &= E\left[\sum_{j=1}^N u_j v_j \phi_{i,j}^2 + \sum_{r \neq s} u_r v_s \phi_{i,r}\phi_{i,s}\right] \\ &= \sum_{j=1}^N u_j v_j E[\phi_{i,j}^2] + \sum_{r \neq s} u_r v_s E[\phi_{i,r}]E[\phi_{i,s}] \\ &= a^2 \mathbf{u}^T\mathbf{v} \end{aligned}$$

$$E[g] = E\left[\frac{1}{M}\sum_{i=1}^M \delta_i\right] = E[\delta_i] = \mathbf{u}^T\mathbf{v} \quad (7)$$

Further,

$$\begin{aligned} E[\delta_i^2] = E&\left[\left(\sum_{j=1}^N u_j v_j \phi_{i,j}^2\right)^2 + \left(\sum_{r \neq s} u_r v_s \phi_{i,r}\phi_{i,s}\right)^2\right] \\ &+ 2E\left[\left(\sum_{j=1}^N u_j v_j \phi_{i,j}^2\right)\left(\sum_{r \neq s} u_r v_s \phi_{i,r}\phi_{i,s}\right)\right] \\ =&\sum_{j=1}^N u_j^2 v_j^2 E[\phi_{i,j}^4] + 2\sum_{r<s} u_r v_s E[\phi_{i,r}^2]E[\phi_{i,s}^2] \\ &+ \sum_{r \neq s} u_r^2 v_s^2 E[\phi_{i,r}^2]E[\phi_{i,s}^2] \\ &+ 2\sum_{r<s} u_r v_s u_s v_r E[\phi_{i,r}^2]E[\phi_{i,s}^2] \\ =&\ a^4 \sum_{j=1}^N u_j^2 v_j^2 + 2a^4 \sum_{r<s} u_r v_s u_s v_r \\ &+ a^4 \sum_{r \neq s} u_r^2 v_s^2 + 2a^4 \sum_{r<s} u_r v_s u_s v_r \\ =&\ a^4 (\sum_{j=1}^N u_j^2 v_j^2 + 2\sum_{r \neq s} u_r v_r u_s v_s + \sum_{r \neq s} u_r^2 v_s^2) \\ =&\ 2a^4 (\sum_{j=1}^N u_j^2 v_j^2 + \sum_{r \neq s} u_r v_r u_s v_s) \\ &+ a^4 (\sum_{j=1}^N u_j^2 v_j^2 + \sum_{r \neq s} u_r^2 v_s^2) - 2\sum_{j=1}^N u_j^2 v_j^2 \\ =&\ 2a^4 (\mathbf{u}^T\mathbf{v})^2 + a^4 \|\mathbf{u}\|_2^2\|\mathbf{v}\|_2^2 - 2a^4 \sum_{j=1}^N u_j^2 v_j^2 \end{aligned} \quad (8)$$

$$\begin{aligned} Var(\delta_i) &= E[\delta_i^2] - E^2[\delta_i] \\ &= 2a^4(\mathbf{u}^T\mathbf{v})^2 + a^4\|\mathbf{u}\|_2^2\|\mathbf{v}\|_2^2 \\ &\quad - 2a^4\sum_{j=1}^{N} u_j^2 v_j^2 - a^4(\mathbf{u}^T\mathbf{v})^2 \\ &= a^4(\mathbf{u}^T\mathbf{v})^2 + a^4\|\mathbf{u}\|_2^2\|\mathbf{v}\|_2^2 - 2a^4\sum_{j=1}^{N} u_j^2 v_j^2 \end{aligned} \tag{9}$$

Therefore, we have

$$\begin{aligned} Var(\mathbf{x}^T\mathbf{y}) = Var(g) &= \frac{1}{M^2}\sum_{i=1}^{M} Var(\delta_i) \\ &= \frac{a^4}{M}\left((\mathbf{u}^T\mathbf{v})^2 + \|\mathbf{u}\|_2^2\|\mathbf{v}\|_2^2 - 2\sum_{j=1}^{N} u_j^2 v_j^2\right) \end{aligned} \tag{10}$$

Theorem 1: Consider a data vector $\mathbf{u} \in \mathbb{R}^N$ and any set of vectors $V = \{\mathbf{v}_1, \cdots, \mathbf{v}_n\} \subset \mathbb{R}^N$. Assume a sparse random matrix $\Phi \in \mathbb{R}^{M\times N}$ satisfies the conditions in Eq. (5) with the degree of sparsity T. Given $\epsilon > 0$, define

$$M = O\left(\frac{2}{N^4\epsilon^2}(T+1)^4(1+\xi)\log N\right) \tag{11}$$

Then, with probability at least $1-N^{-\xi}$, the random projections $\frac{1}{\sqrt{M}}\Phi\mathbf{u}$ and $\frac{1}{\sqrt{M}}\Phi\mathbf{v}_i$ can generate an estimate $\hat{\theta}_i$ for $\mathbf{u}^T\mathbf{v}_i$ satisfying

$$|\hat{\theta}_i - \mathbf{u}^T\mathbf{v}_i| \le \epsilon\|\mathbf{u}\|_2\|\mathbf{v}_i\|_2 \tag{12}$$

for all $i = 1, 2, ..., N$.

A formal proof of Theorem 1 can be obtained by following the analysis in [10] and is omitted in this paper.

According to Theorem 1, if the number of projections satisfies $M = O\left(\frac{2a^4}{\epsilon^2}(1+\xi)\log N\right)$, the random projection Φ can preserve all pairwise inner products within an approximation error ϵ, with probability at least $1 - N^{-\xi}$. In our scheme, the number of projections M is equal to λ^T. It means that, to control the reconstruction error within a given ϵ with probability no less than $1 - N^{-\xi}$, the relationship between T and λ must satisfy:

$$\lambda^T = O\left(\frac{2}{N^4\epsilon^2}(T+1)^4(1+\xi)\log N\right) \tag{13}$$

V. SIMULATION RESULTS

In this section, we present numerical results to demonstrate the performance of the proposed data gathering algorithm. Consider a grid network containing 16×16 square cells with same side length. There are 256 nodes that are randomly deployed into these square areas so that each cell contains exactly one node. Assume each node can communicate with at least 5 neighboring nodes. All the nodes are indexed by $i \in \{1, 2, \dots, N\}$, with x_i representing the reading of node i. The test signal $\mathbf{x}$ is produced to have a sparsity of $K = 20$, and the non-zeros entries in $\mathbf{x}$ are Gaussian distributed $\mathcal{N}(0, 1)$. The signal reconstruction algorithm adopted is orthogonal matching pursuit (OMP) [14] algorithm. In addition, the average relative error of reconstruction signal $\hat{\mathbf{x}}$ is defined as:

$$\varepsilon = \sum_{i=1}^{N}\frac{1}{N}\frac{\|\mathbf{x} - \hat{\mathbf{x}}_i\|_2^2}{\|\mathbf{x}\|_2^2} \tag{14}$$

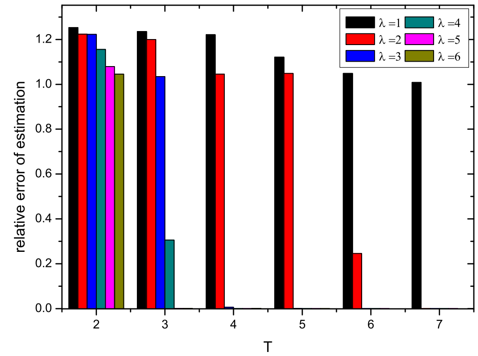

Fig. 1. Impact of T and λ on reconstruction quality

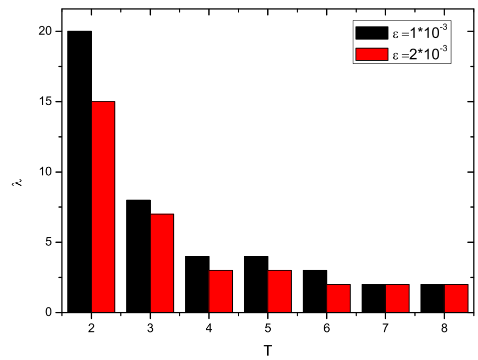

Fig. 2. Trade-off between T and λ

Fig. 1 shows the impact of the lifetime T and the number of randomly chosen neighbors λ on the reconstruction quality. It is observed that the reconstruction quality of $\mathbf{x}$ is improved with the increase of T or λ. When we fix λ and only enlarge T, the sparsity of the projection vector would gradually reduce. Therefore, more readings can be sampled in each projection, thus providing more information for reconstruction. On the other hand, when we keep T intact and just increase λ, each sensor will send the data packet to more neighbors in each forwarding. As a result, the sensor will receive more packets, i.e., obtain more random projections. It also leads to better reconstruction quality. Specifically, when $T > 4$ and $\lambda > 3$, the reconstruction error approximates to zero.

Fig. 2 plots the trade-off between T and λ for a desired accuracy of reconstruction. Namely, for a given approximation error ε, when we increase the value of T, the minimum λ required can be oppositely reduced, and vice versa. This model provides a very useful guideline on how to select T and λ in a practical system.

In Fig. 3, we show the relationship between the number of

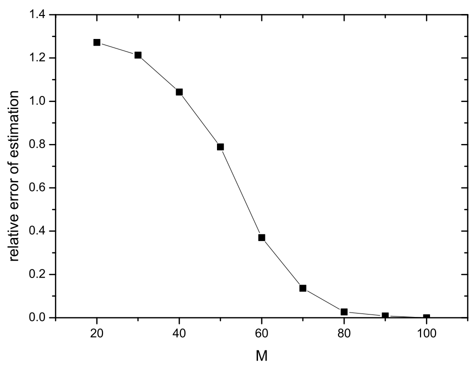

Fig. 3. Impact of M on reconstruction quality

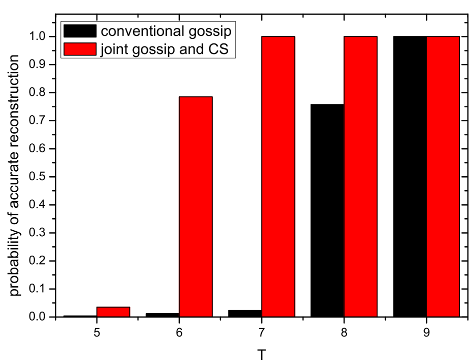

Fig. 4. Probability of accurate reconstruction

sparse projections M and the average relative error ε. It can be seen that the average error ε decreases as M increases. Since M is If the number of sparse projections is more than 80, we can perfectly recover the original signal with estimation error $\varepsilon \leq 10^{-3}$.

Fig. 4 compares the performance of the proposed method with the conventional random gossip algorithm in which CS is not employed and the data is forwarded in raw format. Here we have $\lambda = 3$. In this case, if a sensor can obtain a estimation $\hat{\mathbf{x}}$ with $\varepsilon \leq 10^{-3}$, it is supposed to achieve an accurate reconstruction. The proportion of the sensors which have an accurate reconstruction is defined as the probability of accurate reconstruction. It can be found that, when transmitting the same number of data packets, the reconstruction quality acquired from the proposed scheme is obviously better than the conventional random gossip. In other words, for a given reconstruction quality, the overall communication cost of our approach is much less than that of traditional one.

VI. Conclusions

This paper studied energy-efficient global information gathering at a single point in WSNs. To reduce both computation and communication cost, we jointed sparse random projections with randomized gossiping, and presented a compressive sensing based distributed data collection scheme. It constructed projection matrix in accordance with the transmission structure of the combined data packet, thus generating sparse random projections. Also, the trade-off between two key parameters, i.e., the packet lifetime and the number of random chosen neighbors, is theoretically modeled. Simulation results show that our approach outperforms the tradition gossip algorithm with respect to communication overhead as well as reconstruction quality. In our future work, further investigation may be made to extend the proposed method to image and video signal acquisition.

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