Energy-Balanced Compressive Data Gathering in Wireless Sensor Networks

Cuicui Lv^{a,*}, Qiang Wang^{a,*}, Wenjie Yan^b, Yi Shen^a

^aDepartment of Control Science and Engineering, Harbin Institute of Technology, Harbin, China

^bSchool of Computer Science and Engineering, Hebei University of Technology, Tianjin, China

Abstract

Compressive Sensing(CS) can use fewer samples to recover a great number of original data, which have a sparse representation in a proper basis. For energy-constrained Wireless Sensor Networks(WSNs), CS provides an effective data gathering approach. Gaussian random matrix satisfies Restricted Isometry Property(RIP) with high probability. The class of matrices are usually selected as the measurement matrix for compressive data gathering in WSNs. However, they are dense, and the computational complexity is higher. On the other side, sparse binary matrix with a fixed number of nonzero entries in each column satisfies RIP-1 property. Due to the higher sparsity, the class of sparse binary matrix is chosen as the measurement matrix in the paper. In order to adapt to the dynamic change of network topology, we design a mobile agent based compressive data gathering algorithm (MA-Greedy), where each sensor node is uniformly visited in M measurements. Coefficient of Variation(CV) is proposed to evaluate the balance of energy consumption. The numerical experiments show the proposed algorithm is superior to other algorithms(i.e. non-CS, plain-CS, Hybrid-CS, and Distributed Compressive Sparse Sampling(DCSS)) in terms of energy balance. Moreover, we discover the performance of reconstructing sparse zero-one signals by sparse binary matrix, which is used in the proposed MA-Greedy algorithm, is better than that by Gaussian random matrix when Basis Pursuit(BP) algorithm is used for signal recovery.

Keywords:

compressive sensing, wireless sensor networks, sparse binary matrix, mobile agent, energy balance

1. Introduction

Wireless sensor networks(WSNs) consist of a large number of sensor nodes. Their task is to periodically gather data and transmit the data to sink node by wireless communication Yick et al. (2008). Sensor nodes are usually powered by batteries. The calculation ability and communication ability are limited Anastasi et al. (2009). Once deployed, they may receive little maintenance. In the complex and inaccessible environment monitoring, it is hard to replenish energy. How to gather the data in an energy-efficient way becomes the most urgent question for energy-constrained WSNs.

In conventional sampling approaches, the signals are first uniformly sampled at or above the Nyquist rate, which requires a minimum number of samples, and compressed during the transmission. The approach can eliminate the redundant information and reduce traffic burden. But most samples are thrown away in the data compression, wasting tremendous time and energy. A novel framework for signal acquisition Zhao and Huang (2012), Compressive Sensing(CS), has emerged and received significant attention from researchers. In CS, sampling and compression are simultaneous. It only samples a part of data which aren't thrown away in the data compression. Compared with Shannon's sampling theory, CS enables a potentially large reduction in the number of samples and the computation costs.

When the signals are sparse or compressible in a suitable basis or dictionary, CS theory can be used to recover the signals from a small set of linear, non-adaptive measurements Candès (2006); Donoho (2006); Baraniuk (2007). Since the signals are linearly projected on the measurement matrix for measurements, the computational complexity of encoding is lower. Besides, encoding and decoding are independent. Decoding is operated at sink node, further reducing energy consumption of sensor nodes. So CS provides an efficient approach for data gathering in WSNs.

In the burst events monitoring Xie et al. (2011), compared with multitudinous sensor nodes, the number of sensor nodes that have monitored the burst events happening is very sparse. CS can be applied to sparse data gathering in WSNs. In the paper, we mainly address the energy balance problem of compressive data gathering in WSNs. Because the network topology changes dynamically, compressive data gathering algorithm is required to have good robustness. Mobile agent is intelligent and it doesn't need to keep all the sensor nodes synchronized. It is particularly attractive in this problem. We adopt mobile agent based compressive data gathering approach to transmit the sensed data. The main contributions of the paper are as follows.

- (1) We discuss compressive data gathering in WSNs. Dense measurement matrices require all the sensor nodes to participate in data gathering, leading to more energy consumption. We choose sparse binary matrix as the measurement matrix in CS. Because the number of nonzero entries in sparse binary matrix is less than that of zero entries, it leads

*Corresponding author

Email address: lvcuicui@hit.edu.cn(Cuicui Lv); wangqiang@hit.edu.cn (Qiang Wang)

to a significant reduction in computational complexity and storage requirements.

- (2) In CS paradigm, we first use mobile agent to gather sparse data in WSNs. Like Minimum Traveling Salesman Problem(MTSP), the path design of mobile agent is a Constrained Minimum Traveling Salesman Problem(CMTSP), which is NP-hard. We put forward a compressive data gathering approach based on greedy algorithm.
- (3) The total energy consumption of WSNs is the major measure metric in the existing literatures. There exists some sensor nodes that relay a large number of data from others in the tree-type structure. Their energy consumption is much more than others. When the energy of these sensor nodes is depleted, the network may be disconnected, which can shorten the network lifetime. That is, the minimum energy consumption doesn't guarantee that energy consumption of each sensor node is more balanced. To evaluate the balance of energy consumption, we propose Coefficient of Variation(CV) and compare the performance of proposed MA-Greedy algorithm with that of other data gathering algorithms.

The remainder of the paper is organized as follows. In Section 2, we review related works about compressive data gathering in WSNs. In Section 3, we give a brief overview of CS, and describe the network model. Coefficient of Variation(CV) in WSNs is defined and mobile agent based compressive data gathering algorithm(MA-Greedy algorithm) is presented in Section 4. In Section 5, we conduct the experiments to demonstrate the performance of MA-Greedy algorithm in terms of energy balance. Section 6 concludes the paper. Table 1 summarizes the notations in the paper.

2. Related works

In recent years, the application of CS to data gathering in WSNs has been receiving increasing attention. An early application of CS in WSNs is Bajwa et al. (2007), where a distributed joint source-channel communication architecture was proposed for energy-efficient estimation of sensor field data, and sensor nodes synchronously transmitted the sensed data to sink node in a single hop way. While it doesn't consider how to use CS in multi-hop communication.

For multi-hop networking scenarios, CS in conjunction with routing was exploited in Quer et al. (2009), where random projections of sensed data were transmitted to sink node. Routing matrix was the measurement matrix whose coefficients were generated by the same pseudo-random number generator at the sensor nodes. Unlike the contribution in Quer et al. (2009), Lee et al. (2009) considered the communication cost and presented a centralized, greedy algorithm for energy efficient data gathering in WSNs, but the results showed the effectiveness of CS was limited. Luo et al. (2009) first analyzed traditional data gathering and Compressive Data Gathering(CDG) in the chain-type topology. Then they presented the first complete design to apply CS to sensor data gathering

Table 1: Summary of notations used in the paper

notations	definitions
$G(V, E)$	the undirected graph $G(V, E)$
V	the set of vertices in $G(V, E)$
E	the set of edges in $G(V, E)$
s_0	sink node
s_i	sensor node with ID $i(1 \leq i \leq N)$
e_{ij}	edge between s_i and s_j
$neig(s_i)$	the neighborhood nodes of s_i
x	a sparse signal of size $N \times 1$
Ψ	the orthonormal basis
Θ	the coefficient vector
k	the sparsity of x
M	the number of measurements
$\Phi_{M \times N}$	the measurement matrix of size $M \times N$
y	the measurement vector
d	the number of nonzero entries
IN_i	the interest node of mobile agent with ID i
E_{Tx}	energy consumption of transmitting the information
E_{Rx}	energy consumption of receiving the information
d_0	the given threshold
L	the size of the information
E_{elec}	the parameter of transmitting/receiving circuit
E_{amp}	the parameter of the amplifier in transmitting circuit
n	the path loss factor
R	communication radius
CV	coefficient of variation
σ	standard deviation
$\bar{E}$	the average energy consumption of WSNs
$\hat{x}$	the reconstruction signal of x
ε	relative error

in large-scale WSNs. Each sensor node transmitted M messages. Tree-type structure was chosen to transmit the random projections. When sink node received M weighted sums of random projections, reconstruction algorithm was used to recover the original signal. Directly CS coding on each sensor node was called plain CS aggregation(plain-CS) in Xiang et al. (2013), where Xiang et al. (2013) proposed a data aggregation technique called Hybrid CS aggregation(Hybrid-CS). Only when the outgoing data flows of sensor nodes were no less than the number M of measurements, sensor nodes started CS coding. Minimum Spanning Tree(MST) and data aggregation were jointed to minimize the total energy consumption. Fazel et al. (2011) introduced the application of Random Access Compressed Sensing(RACS) in underwater environment monitoring. RACS employed random sensing for the sampling procedure and a simple random access for the channel access phase to prolong the network lifetime. Chen and Wassell (2011) proposed an energy-efficient signal acquisition approach for monitoring 1-D environmental information. Random sampling and the Sampling Rate Indicator(SRI) feedback were introduced. Random sampling could trade off the randomization and computational complexity. SRI feedback maintained the reconstruction quality and reduced energy consumption. Mamaghanian et al. (2011) quantified the potential of CS for energy-efficient ECG data acquisition and compression on resource-constrained Wireless Body Sensor Networks(WBSN) platforms. The implementation of Gaussian random matrix was too complex, and time consuming. It was certainly not a real-

time task for the MSP430. They explored three different methods, where sparse sensing matrix was superior in terms of execution time.

Dense random matrices are chosen as the measurement matrix in most available literatures. As described above, the implementation of dense random matrices is too complex and time consuming. Because of lower complexity and higher sparsity, sparse binary matrix is exploited as the measurement matrix. Intelligent mobile agent is introduced for compressive data gathering in WSNs.

3. Problem description and network model

In the section, we first review CS theory, and analyze two classes of CS measurement matrices, dense random matrices and sparse random matrices. Finally mobile agent based network model is given.

3.1. CS Overview and design of sparse binary matrix

Suppose a WSN consists of N sensor nodes and one sink node. Each sensor node has a random ID. WSN is abstracted to an undirected graph $G(V, E)$, where V and E denote the set of vertices and edges, respectively. V is written as $V = \{s_0, s_1, \dots, s_i, \dots, s_N\}$, where s_0 denotes sink node and s_i is sensor node with ID i ($1 \leq i \leq N$). If two sensor nodes s_i and s_j can communicate with each other, edge e_{ij} exists. E is expressed as $E = \{e_{ij} | 1 \leq i < j \leq N\}$.

The data reading of s_i is x_i , and the data readings x of N sensor nodes are a column vector $x = [x_1, x_2, \dots, x_i, \dots, x_N]^T$ of size $N \times 1$. If x has a sparse or compressible representation in the orthonormal basis $\Psi \in \mathbb{R}^{N \times N}$, x can be expressed as

$$x = \Psi \Theta \quad (1)$$

where $\Theta \in \mathbb{R}^{N \times 1}$ is the coefficient vector of x . $\|\Theta\|_0$ denotes the number of nonzero entries in Θ . If $\|\Theta\|_0 = k$ ($k \ll N$), x is k sparse.

The linear measurement vector $y = [y_1, y_2, \dots, y_i, \dots, y_M]^T$ is acquired by

$$y = \Phi x = \Phi \Psi \Theta \quad (2)$$

where $\Phi \in \mathbb{R}^{M \times N}$ ($M \ll N$) is the measurement matrix denoted as $\Phi_{M \times N}$. If $\Phi_{M \times N} \Psi$ satisfies RIP, it is sufficient to recover the signal x from a small number of linear measurements. Furthermore, the number M of measurements needs to meet the condition in Eq.(3), where c is a positive constant.

$$M \geq c \cdot k \cdot \log(N/k) \quad (3)$$

Dense random matrices, such as independent and identically distributed Gaussian random matrix or Bernoulli matrix, satisfy RIP with overwhelming probability and they are usually selected as the measurement matrix $\Phi_{M \times N}$ in WSNs. However, it is complex to implement them. In addition, most entries in dense random matrices are non-zero. This requires a large number of sensor nodes to participate in compressive data gathering, leading to more energy consumption.

Another class of matrices are called sparse random matrices. Wang et al. (2007) showed sparse random matrices were sufficient for data recovery, and the performance was comparable to the optimal k -term approximation. Sparse binary matrix is in this category. Li and Qi (2013) analyzed the relation between expander graph and sparse binary matrix in detail. Extensive experiments on both synthetic and real data sets showed CS recovery accuracy by sparse binary matrix outperformed existing sparse random matrices in Wang et al. (2007).

For the design of sparse binary matrix $\Phi_{M \times N}$, we randomly choose d locations in each column of $\Phi_{M \times N}$. Let the entries on these locations be one and the other entries are zero. Such matrices have a one-to-one correspondence with the adjacency matrices of fixed left degree expander graph, and they can be constructed explicitly by expander graphs Xu and Hassibi (2007); Jafarpour et al. (2009).

3.2. Mobile agent based network model

Each row of $\Phi_{M \times N}$ expresses a path to sink node. In Wang et al. (2007), each row is assigned to a projection node. For a WSN with N sensor nodes, each sensor node is selected as the projection nodes with probability of M/N in M measurements. The different projection nodes lead to different energy consumption, so the selection of projection nodes can affect energy consumption. Mobile agent is a special kind of software or computer program. It can migrate between nodes in a network to perform a task(or tasks) autonomously and intelligently Chen et al. (2007). Different from the approach in Wang et al. (2007), the paper uses mobile agent for compressive data gathering in WSNs.

Suppose sparse binary matrix is $\Phi_{M \times N}$. Sink node assigns mobile agents with different IDs to each row in $\Phi_{M \times N}$. If the entries in the i th ($1 \leq i \leq M$) row are $[\phi_{i1}, \phi_{i2}, \phi_{i3}, \dots, \phi_{ij}, \dots, \phi_{iN}]$, mobile agent with ID i leaves sink node and visits the interest nodes IN_i whose coefficients ϕ_{ij} ($1 \leq j \leq N$) are nonzero. The nodes in IN_i are visited by the proposed MA-Greedy algorithm in Section 4. When mobile agent with ID i migrates to an interest node s_j , it acquires the data reading x_j of s_j and gets a projection $\phi_{ij} \cdot x_j$. Then the mobile agent will carry the weighted sums $\sum \phi_{ij} \cdot x_j$ of projection to the next interest node, which hasn't been visited. After all the interest nodes in the row are visited, mobile agent carries the measurement $y_i = \sum_{j=1}^N \phi_{ij} \cdot x_j$ to sink node. Through M measurements, sink node gets the measurement vector $y = [y_1, y_2, \dots, y_i, \dots, y_M]^T$. According to CS reconstruction algorithms, sink node can recover the original data readings x of sensor nodes from the measurement vector y .

4. Compressive data gathering algorithm

In the section, we define Coefficient of Variation(CV) in WSNs. Describe mobile agent based compressive data gathering algorithm(MA-Greedy algorithm) and analyze its time complexity.

4.1. Coefficient of Variation(CV)

Energy consumption $E_{Tx}(i)$ for L bits information transmitted by s_i over the distance d_i is given in Eq.(4).

$$E_{Tx}(i) = (E_{elec} + E_{amp} \times d_i^n) \times L \quad (4)$$

where E_{elec} and E_{amp} are the parameters of transmitting/receiving circuit and the amplifier in transmitting circuit Abdulla et al. (2012). n is the path loss factor, ranging from 2 to 4. The value of n depends on the given threshold d_0 . If d_i is less than d_0 , the free space channel model(d_i^2 power loss) is used. Otherwise, the multipath channel model(d_i^4 power loss) is used Heinzelman et al. (2002).

$E_{Rx}(i)$ is energy consumption of s_i receiving L bits information.

$$E_{Rx}(i) = E_{elec} \times L \quad (5)$$

The total energy consumption of s_i is $E_{Total}(i)$.

$$E_{Total}(i) = E_{Tx}(i) + E_{Rx}(i) \quad (6)$$

In order to evaluate the difference of the total energy consumption among sensor nodes, we define Coefficient of Variation (CV) in WSNs.

$$CV = \frac{\sigma}{\bar{E}} \quad (7)$$

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^N (E_{Total}(i) - \bar{E})^2} \quad (8)$$

$$\bar{E} = \frac{1}{N} \sum_{i=1}^N E_{Total}(i) \quad (9)$$

where σ is standard deviation, and $\bar{E}$ is the average energy consumption of WSNs.

If the value of CV is smaller, the total energy consumption of each sensor node is more concentrated, and the difference of the total energy consumption among sensor nodes is smaller. In other words, the smaller the value of CV is, the more balanced the total energy consumption among sensor nodes is.

4.2. Compressive data gathering algorithm

In general, the undirected network topology graph $G(V, E)$ isn't a complete graph. In order to make mobile agents move from one node to another nodes, the degree of each node (i.e. the number of link edges to the node) is at least two. In the condition, the network may be disconnected. The network connectivity must be guaranteed such that mobile agents can return to the original point after visiting their interest nodes. We confirm the network connectivity by two methods. One method is the construction of spanning trees in $G(V, E)$. If $G(V, E)$ contains a spanning tree, $G(V, E)$ is connected. Otherwise, $G(V, E)$ is disconnected. The other one is Breadth First Search(BFS). If every node can be visited by BFS, $G(V, E)$ is connected. Or $G(V, E)$ is disconnected. When $G(V, E)$ is disconnected, other nodes are added or the communication radius R is increased until $G(V, E)$ is connected.

If $G(V, E)$ is connected and the degree of each node is at least one, there must be Minimum Spanning Tree(MST). There will be no loops in MST unless some edges are added. In this case, mobile agents can also visit their interest nodes. But a large number of nodes will be visited for many times, which results in more energy consumption. So we require that the degree of each node is at least two.

Theorem 1. *If $G(V, E)$ is connected and the degree of each node is at least two, mobile agents can return to sink node after visiting the interest nodes by the loops.*

Proof. The number of sensor nodes and the link edges in WSNs are finite, so $G(V, E)$ is finite. There must exist a tremendous path P in $G(V, E)$ West and West (2001). Let u be a terminal vertex in P . Then all neighborhood nodes of u must be in P . Because the degree of u is at least two, the neighborhood node v , making the link edge e_{uv} between u and v not be in P , of u exists. e_{uv} and the path from v to u in P form a loop. In other words, if the degree of each node is at least two, $G(V, E)$ contains at least a loop. In the monitored area, the interest nodes are distributed uniformly. Mobile agents leave sink node to visit them and finally return to sink node. Their path design needs the loops. However, the isolated loops may exist. So $G(V, E)$ is required to be connected. Under the two conditions, mobile agents can return to sink node after visiting their interest nodes. $\square$

Theorem 2. *If sparse binary matrix is $\Phi_{M \times N}$ and mobile agents with different IDs visit their interest nodes, their path design is NP-hard.*

Proof. Each column of $\Phi_{M \times N}$ has d nonzero entries. If N entries in the i th row of $\Phi_{M \times N}$ are nonzero and N sensor nodes can communicate with each other, the path design of mobile agent with ID i is in close proximity to Travelling Salesman Problem(TSP), which is NP-hard. This is a particular case of the path design of mobile agent. Generally speaking, mobile agent only visits a few of sensor nodes rather than all sensor nodes. But if these sensor nodes can communicate with each other, the path design of mobile agent is also similar to TSP. Otherwise, other sensor nodes that aren't the interest nodes are added to connect the network. In a word, the path design of mobile agents can be regarded as CMTSP. Because the path design of mobile agents in the particular case, where all the interest nodes can communicate with each other, is NP-hard, CMTSP is NP-hard. $\square$

When the network topology is a complete graph, Qi et al. studied the dynamic path planning of mobile agents, and put forward Local closest first(LCF) and global closest first(GCF)Qi and Wang (2001). In GCF, the current node chose the closest node to the center node as the next node in each iteration, leading to path inflections and extra energy consumption. Its performance was worse than LCF. As described in section III, each mobile agent must visit its interest nodes. How to visit the interest nodes is a Constrained Minimum Traveling Salesman Problem(CMTSP), and CMTSP is NP-hard. Inspired by

Algorithm 2 MA-Greedy-II

Input:
 sparse binary matrix $\Phi_{M \times N}$
 the partial path of MA with ID i ($1 \leq i \leq M$)

Output:
 the complete paths of MAs

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1: for each row  $i$  ( $1 \leq i \leq M$ ) in  $\Phi_{M \times N}$  do
2:   If the final node visited by MA with ID  $i$  is  $s_0$ , MA-Greedy-II ends. Otherwise, the
   final node is marked as  $s_j$ . MA conducts the following steps.
3:   if  $neig(s_j) \in IN_i$  and  $neig(s_j)$  aren't visited then
4:     MA selects the closest  $neig(s_j)$  as the next node.
5:   else
6:     MA chooses the closest node that isn't visited in  $IN_i$  as  $D_4$ .
7:     while  $D_4$  isn't visited do
8:       if there're the unvisited  $neig(s_j)$  then
9:         Repeat the same strategy as the step6~step9 in MA-Greedy-I and update
         the current node to  $s_j$ .
10:      else
11:        Repeat the same strategy as the step26~step32 in MA-Greedy-I. Update
        the current node to  $s_j$  and search the unmarked  $neig(s_j)$ .
12:      if all the  $neig(s_j)$  are marked then
13:        If  $neig(D_4) \in neig(s_j)$ , MA visits  $D_4$  via the closest  $neig(D_4)$  to  $s_j$ .
        Otherwise, MA uses Floyd-Warshall algorithm to visit  $D_4$ .
14:      else
15:        if the unmarked  $neig(s_j) \in neig(D_4)$  then
16:          MA arrives at  $D_4$  via the closest  $neig(s_j)$  to  $s_j$ .
17:        else
18:          MA chooses the closest  $neig(s_j)$  to  $D_4$  as the next node and up-
          dates the current node to  $s_j$ .
19:        end if
20:      end if
21:    end while
22:  end if
23: end if
24: Repeat the same strategy as the step40~step46 in MA-Greedy-I until MA with ID
   $i$  returns to  $s_0$ .
25: end for

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as sort algorithm. MA-Greedy algorithm contains M measurements. The average time complexity of MA-Greedy algorithm is $O(M\tau_{max}\log\tau_{max})$, where τ_{max} is the maximal number of the nodes in IN_i .

In the worst case, all the nodes in IN_i can't communicate with each other, and other nodes which aren't the interest nodes are added in the network. All the nodes participate in data gathering and Floyd-Warshall algorithm is used. The time complexity of MA-Greedy algorithm is $O(MN^3)$.

We give an example of MA-Greedy algorithm. Construct a sparse binary matrix $\Phi_{50 \times 100}$, where d is 4. According to MA-Greedy-I, we determine the entries in IN_1 , IN_{27} , IN_{37} and IN_{47} . Then mobile agents visit the nodes in IN_i by the paths designed by MA-Greedy algorithm. As shown in Fig.2, the magenta solid dots are the nodes in IN_i . The cyan solid dots are the other nodes that aren't the interest nodes and they are added to guarantee the network connectivity. Table 2 lists the paths of four mobile agents.

$$IN_1 = \{6, 16, 17, 27, 43, 74, 78, 82, 89\}$$

...

$$IN_{27} = \{13, 19, 23, 35, 39, 46, 50, 52, 67, 97\}$$

...

$$IN_{37} = \{5, 37, 44, 71, 74, 81, 91\}$$

...

$$IN_{47} = \{23, 42, 51, 73, 75, 81, 93, 97\}$$

...

Fig. 2. The paths designed by MA-Greedy algorithm: (a)The path of mobile agent with ID 1 (b)The path of mobile agent with ID 27 (c)The path of mobile agent with ID 37 (d)The path of mobile agent with ID 47

Table 2: The paths of four mobile agents

Mobile agent with ID	Paths of mobile agent
1	89-43-6-17-3-53-82-78-16-27-24-74
27	39-84-67-11-50-13-52-58-19-97-35-46-57-36-20-23-47-39
37	71-74-37-31-39-44-18-11-5-15-81-91-71
47	76-73-93-97-81-51-61-72-75-55-42-8-1-69-23-77-85

5. Experiment results and analysis

We conduct two experiments to demonstrate the effectiveness of proposed algorithm. In the first experiment, we compare proposed MA-Greedy algorithm with other data gathering algorithms in terms of CV. The second experiment shows the results of reconstructing sparse signals by sparse binary matrix. In addition, the performance of signal reconstruction by sparse binary matrix is compared with that by Gaussian random matrix.

5.1. Experiment Setup

In the experiment, the threshold d_0 and communication radius R are set as 50m and 30m, respectively. Because the communication distance between nodes is less than or equal to R , free space channel model is used. Experimental parameters are listed in Table 3.

100 sensor nodes are deployed in the area 100m×100m. They are stationary and their locations are known. Fig.3 shows two random uniform layouts of sensor nodes. The location of sink node may have an effect on the balance of energy consumption Safa et al. (2014). Two cases, i.e., sink node is in the center and

Table 3: Experimental parameters

parameters	value
R	30m
E_{elec}	1J/bit
E_{amp}	1J/bit/m ²
n	2
L	1bit
d	4

at the corner, are taken into account. In the following experiments, the center and the corner are set at the locations (50,50) and (0,0) of the area in Fig.3, respectively.

Fig. 3. Two random uniform layouts of sensor nodes: (a)The first random uniform layout of sensor nodes (b)The second random uniform layout of sensor nodes

According to the two random uniform layouts of sensor nodes and two sink node layouts, we compare CV of the proposed MA-Greedy algorithm with that of the other four data gathering algorithms (i.e. non-CS, plain-CS, Hybrid-CS, and DCSS). In non-CS, the original data(the data without compression) are transmitted through tree-type structure. In plain-CS and Hybrid-CS, the measurement matrix is Gaussian random matrix. However, the measurement matrix in DCSS is sparse binary matrix which is the same as that used in MA-Greedy algorithm.

5.2. Energy balance performance analysis

The number N of sensor nodes is set as 100. If the value of M is smaller, sink node gets fewer measurements and the reconstruction performance will decline. Larger M goes against compressive data gathering. And the value of M affects the energy efficiency of Hybrid-CS. In order to observe the changes of CV in Hybrid-CS and guarantee the sparsity of sparse binary matrix, M is set to a smaller value from the beginning. Furthermore, the measurement matrices in the experiment are Gaussian random matrix and sparse binary matrix. Different measurement matrices can make CV of compressive data gathering algorithms different. So for each value of M , we test ten groups of the measurement matrices. The measurement matrices with the minimal CV value are used for compressive data gathering. When sink node is in the center of the area, Fig.4(a) and Fig.4(b) depict the changes of CV in the two random uniform layouts, respectively. It can be seen that CV of MA-greedy algorithm is the minimal in the five data gathering algorithms.

The proposed MA-Greedy algorithm uniformly visits each sensor node, which makes total energy consumption of each sensor node is more balanced.

Fig. 4. The changes of CV with the increase of M for sink node in the center: (a)The first random uniform layout (b)The second random uniform layout

In non-CS, each sensor node transmits the original data to next node along the MST based path. The leaf nodes that don't relay the data from other sensor nodes are far away from sink node. Their data are forwarded to sink node by some intermediate sensor nodes, which makes traffic load of the intermediate sensor nodes heavier, especially sensor nodes around sink node. Total energy consumption between them has a great difference, resulting in larger CV. As denoted in two figures, CV of non-CS is larger than that of the other four algorithms, that is, the application of CS to data gathering in WSNs can balance total energy consumption of each sensor node.

In plain-CS, data transmission structure is tree-type. Each sensor node sends or receives M random projections(or weighted sums of random projections). On the condition that tree-type structure is invariable, both total energy consumption $E_{Total}(i)$ of each sensor node and the average energy consumption $\bar{E}$ in WSNs are proportional to the size of the random projections(or weighted sums of random projections). With the increase

of M , the number of random projections(or weighted sums of random projections) increases, which makes $E_{Total}(i)$ and the standard deviation σ increase. However, the increasing ratio of $\bar{E}$ and $E_{Total}(i)$ is the same. According to Eq.(7), the ratio $\sigma/\bar{E}$ of standard deviation to the average energy consumption can't vary. Seen from Fig.4(a) and Fig.4(b), CV of plain-CS doesn't change with the value of M .

In Hybrid-CS, the sensor nodes that perform CS coding are called aggregators and the others are forwarders. When the value of M is smaller, the number of sensor nodes starting CS coding is more. As shown in Fig.4, when M is less than 15, most sensor nodes are the aggregators. Because the size of random projections(or weighted sums of random projections) transmitted by the aggregators is the same, the difference of total energy consumption among them is less. CV of Hybrid-CS is smaller than that of DCSS. With the increase of M , the number of the aggregators reduces, and a majority of forwarders send the original data to corresponding aggregators. Before the original data are transmitted to the aggregators, the data transmission structure is similar to non-CS. For different values of M , if the set of aggregators and data transmission structure change less, CV of Hybrid-CS has minor changes. When the value of M changes from 10 to 35, the set of aggregators between the adjacent M has smaller differences, which causes small fluctuations on the CV curve. When the value of M changes from 35 to 55, the CV curves in two figures are linear. This is because the aggregators and forwarders no longer change when M reaches 35. With the increase of M , the probability that each sensor node is selected for projection nodes becomes higher in DCSS. The CV curves of DCSS roughly degrade in two figures.

The number of measurements M is set as 30. In accordance with five data gathering algorithms in Fig.4, Table 4 and Table 5 present the standard deviation σ , the average energy consumption $\bar{E}$ and CV in two random uniform layouts.

Table 4: σ , $\bar{E}$ and CV of five data gathering algorithms in the first random uniform layout

notations	non-CS	plain-CS	Hybrid-CS	DCSS	MA-Greedy
$\sigma(\times 10^3 J)$	0.9127	1.6872	0.9378	6.5424	0.8462
$\bar{E}(\times 10^3 J)$	0.5884	1.7909	0.8203	7.4447	1.3355
CV	1.5512	0.9421	1.1432	0.8788	0.6336

Table 5: σ , $\bar{E}$ and CV of five data gathering algorithms in the second random uniform layout

notations	non-CS	plain-CS	Hybrid-CS	DCSS	MA-Greedy
$\sigma(\times 10^4 J)$	0.1405	0.1537	0.1033	1.0415	0.0924
$\bar{E}(\times 10^4 J)$	0.0776	0.1884	0.0867	0.9068	0.1314
CV	1.8106	0.8158	1.1915	1.1485	0.7032

In order to evaluate the performance of CV , Fig.5(a)~Fig.5(e) show the total energy consumption layouts of 100 sensor nodes in the first random uniform layout. The comparison result of σ between five data gathering algorithms is

$$\sigma_d > \sigma_b > \sigma_c > \sigma_a > \sigma_e \quad (10)$$

where σ_a , σ_b , σ_c , σ_d and σ_e are σ of five data gathering algorithms in Fig.5, respectively.

In probability and statistics, σ is a measure of the data set dispersion. From Table 4, it can be seen the average energy consumption $\bar{E}$ among different data gathering algorithms is different, so σ can't be directly used to evaluate the difference of total energy consumption among sensor nodes. However, CV can eliminate the effect that the difference of $\bar{E}$ has on the difference of the total energy consumption among sensor nodes. The comparison result of CV in Fig.5 is

$$CV_a > CV_c > CV_b > CV_d > CV_e \quad (11)$$

where CV_a , CV_b , CV_c , CV_d and CV_e are CV of five data gathering algorithms in Fig.5, respectively.

The total energy consumption of each sensor node is set on an order of magnitude for comparison. In Fig.5(a)~Fig.5(d), the total energy consumption of a few sensor nodes is significantly larger than that of the others. This is because non-CS, plain-CS and Hybrid-CS use tree-type structure for the data transmission. In the structure, a few sensor nodes send or receive a large number of data, increasing their total energy consumption. In DCSS, there also exist some sensor nodes visited for many times in the shortest path to sink node. In MA-Greedy algorithm, the times each sensor node is visited are almost the same. As shown in Fig.5(e), the total energy consumption layouts of 100 sensor nodes are more uniform than that in Fig.5(a)~Fig.5(d).

When sink node is at the corner of the area, the changes of CV corresponding to two random uniform layouts in Fig.3 are depicted in Fig.6(a) and Fig.6(b). When M ranges from 10 to 40, it can be seen that CS can still make total energy consumption of each sensor node more balanced than non-CS. Because sink node is at the corner, a mass of data flock to the sensor nodes around sink node, which increases their total energy consumption. Compared with sink node layout in Fig.5, sink node layout in Fig.6 is more affected by the boundary effect. In compressive data gathering, the random projections(or the weighted sums of the random projections) must get through sensor nodes around sink node. Meanwhile, the number of these sensor nodes is less than that without the boundary effect, and their total energy consumption increases.

In Hybrid-CS, sensor nodes closer to sink node must be the aggregators. They forward the data from the forwarders and other aggregators. With the increase of M , their total energy consumption is more relative to the forwarders far away from sink node. Total energy consumption among sensor nodes is more imbalanced and the value of CV gets larger. Overall, CV curves in two figures demonstrates upgrade tendency with the increase of M . When the value of M ranges from 10 to 30, larger fluctuations appear on the CV curves of Hybrid-CS. To be specific, only sensor nodes which make the current energy consumption in WSNs less than the foregoing energy consumption become the aggregators. For different values of M , the aggregators and forwarders change. When the set of aggregators between the adjacent M and data transmission structure have large differences, this will cause larger fluctuations on the CV curves.

(a)

(b)

(c)

(d)

9
(e)

Fig. 5. Energy consumption of each sensor node for sink node in the center: (a)non-CS (b)plain-CS (c) Hybrid-CS (d)DCSS (e)MA-Greedy

(a)

(b)

Fig. 6. The changes of CV with the increase of M for sink node at the corner: (a)The random uniform layout (b)The second random uniform layout

In DCSS, the interest nodes transmit the random projections to the appointed projection nodes through the shortest path. After receiving all the random projections, the projection nodes send them to sink node through the shortest path. The aggregation isn't considered in the shortest path. Some sensor nodes can be used repeatedly for many times. The phenomenon that appears in Hybrid-CS also exists in DCSS. However, each sensor node transmits the same number of random projections (or the weighed sums of random projections) in plain-CS. The CV of plain-CS is smaller than that of the two CDG algorithms (DCSS and Hybrid-CS), as depicted in Fig.6(a) and Fig.6(b). Besides that, Hybrid-CS requires to determine the aggregators and forwarders. Its CV is easily affected by the locations of sink node and the value of M .

The proposed MA-Greedy algorithm needn't choose the projection nodes. When M is less than 40, CV of MA-Greedy algorithm is smaller than that of the other four algorithms. That is, total energy consumption of each sensor node is more balanced. But sink node is at the corner, the interest nodes are far away from it. With the increase of M , mobile agent returns to sink node by the more sensor nodes which aren't the interest nodes. Sensor node close to sink node can be repeatedly visited

for many times. When M increases, CV of MA-Greedy algorithm is larger than that of plain-CS. Total energy consumption of each sensor node appears imbalanced. M is set as 25, Table 6 and Table 7 present the standard deviation σ , the average energy consumption $\bar{E}$ and CV in two random uniform layouts.

Table 6: σ , $\bar{E}$ and CV of five data gathering algorithms in the first random uniform layout

notations	non-CS	plain-CS	Hybrid-CS	DCSS	MA-Greedy
$\sigma(\times 10^4 J)$	0.3400	0.1405	0.1152	1.2990	0.1116
$\bar{E}(\times 10^4 J)$	0.1222	0.1524	0.0892	1.1014	0.1416
CV	2.7823	0.9219	1.2915	1.1794	0.7881

Table 7: σ , $\bar{E}$ and CV of five data gathering algorithms in the second random uniform layout

notations	non-CS	plain-CS	Hybrid-CS	DCSS	MA-Greedy
$\sigma(\times 10^4 J)$	0.2169	0.1282	0.1225	1.1912	0.0831
$\bar{E}(\times 10^4 J)$	1.1338	0.1573	0.1000	1.0528	0.1499
CV	1.6211	0.8150	1.4990	1.1315	0.6784

Take the first random uniform layout as an example. The total energy consumption layouts of 100 sensor nodes are shown in Fig.7(a)~Fig.7(e). The comparison result of CV is

$$CV_a > CV_c > CV_d > CV_b > CV_e \quad (12)$$

where CV_a , CV_b , CV_c , CV_d and CV_e are CV of five data gathering algorithms in Fig.7, respectively. CV of MA-Greedy algorithm is the minimum in five data gathering algorithms.

In Fig.7(a) and Fig.7(c), there exists sensor node with ID 16 in the position (2, 6, 0). Seen from Fig.3(a), the sensor node is close to sink node at the corner. Due to tree-type structure, it needs to forward the data from other sensor nodes. Its total energy consumption is larger than others. Plain-CS also uses the similar tree-type structure, so the total energy consumption of the sensor node with ID 16 is the second largest in Fig.7(b). The distance between sensor node with ID 5 and sink node is 29.8703m, which is close to R . Its total energy consumption is the largest in Fig.7(e). For DCSS in Fig.7(d), each projection nodes transmit random projection from interest nodes through the shortest path. Sensor node with ID 5 is in the shortest path to sink node, and its total energy consumption is larger than the great majority of sensor nodes.

From the above, when sink node is in the center of the area, the proposed MA-Greedy algorithm precedes the other four data gathering algorithms in terms of energy balance. If sink node is at the corner of the area, MA-Greedy algorithm has an advantage for smaller M .

5.3. Reconstruction performance of sparse signals

Suppose k burst events happen, they are detected by k sensor nodes. The data readings of the k sensor nodes are one and the data readings of other sensor nodes are zero. The data readings

(a)

(b)

(c)

(d)

(e)

Fig. 7. Energy consumption of each sensor node for sink node at the corner: (a)non-CS (b)plain-CS (c)Hybrid-CS (d)DCSS (e)MA-Greedy

x of all the sensor nodes are k sparse zero-one signals. The signals can be sampled through the measurement matrix in CS. In the experiment, the measurement matrices are Gaussian random matrix and sparse binary matrix, respectively. Ψ is identity matrix. BP is used to reconstruct the signals Berinde et al. (2008); Indyk (2010).

Relative error ε of reconstructing the signals is defined in Eq.(13).

$$\varepsilon = \frac{\|x - \hat{x}\|_2}{\|x\|_2} \quad (13)$$

where x are k sparse signals and $\hat{x}$ are the reconstructed signals. If $\varepsilon \leq 10^{-4}$, we think the signals can be accurately reconstructed. In the following figures, we also draw the percentage of accurately reconstructing x .

Fig. 8. Relative error and percentage of accurate reconstruction versus sparsity k : (a) sink node in the center (b) sink node at the corner

When the number N of sensor nodes is 100 and the value of M is 50, 1000 zero-one signals x which are k sparse are tested. When sink node is in the center and at the corner, Fig.8(a) and Fig.8(b) denote the results of reconstructing x by Gaussian random matrix and sparse binary matrix used in the first random uniform layout, respectively. When k ranges from 1 to 15, k sparse zero-one signals x can be accurately reconstructed by the

Fig. 9. Relative error and percentage of accurate reconstruction versus the number M of measurements: (a) sink node in the center (b) sink node at the corner

two classes of measurement matrices. Seen from Fig.8, with the increase of k , the relative error ε of reconstructing x by sparse binary matrix is smaller than that by Gaussian random matrix. The smaller ε is, the larger the percentage of accurately reconstructing x is. When k ranges from 15 to 40, the percentage of accurately reconstructing x becomes low gradually. Because the value of M is fixed, the smaller k is enough for accurately reconstructing x . But k sparse zero-one signals x with the larger k require more measurements for accurate reconstruction. With the increase of k , ε increases and the percentage of accurate reconstruction descends.

When k is 5 and the number M of measurements changes from 10 to 55, the results of reconstructing sparse zero-one signals x are shown in Fig.9, where the measurement matrices are corresponding to that in Fig.8. When M ranges from 10 to 30, it can be seen that relative error ε of reconstructing x gradually becomes smaller. In Fig.9(a), relative error ε of reconstructing x by Gaussian random matrix increases by 0.0024~0.1707 than that by sparse binary matrix, and the percentage of accurate reconstruction descends by 0.027~0.1390. When M is within the range of 30~55, x can be accurately reconstructed by two classes of measurement matrices. Similar to Fig.9(a), Fig.9(b)

shows the relative error ε of reconstructing x by Gaussian random matrix increases by 0.003~0.1707 than that by sparse binary matrix, and the percentage of accurate reconstruction decreases by 0.027~0.1390. In other words, the curves in Fig.9(a) and Fig.9(b) are almost the same.

As can be seen from Fig.8 and Fig.9, the reconstruction quality by sparse binary matrix is comparable to that by Gaussian random matrix. Under the same conditions, the percentage of accurately reconstructing sparse zero-one signals x by sparse binary matrix is larger than that by Gaussian random matrix. For energy-efficient WSNs, sparse binary matrix is an alternative to Gaussian random matrix for data gathering.

6. Conclusions

The paper studies compressive data gathering in WSNs. Taking into account dynamic change of practical network topology and the feature of mobile agents, we propose a mobile agent based compressive data gathering algorithm(MA-Greedy). The algorithm considers the relation between sparse binary matrix and data gathering. In the best-case scenario, the average time complexity of MA-Greedy algorithm is $O(M\tau_{max}\log\tau_{max})$, where $\tau_{max}(\tau_{max} \leq N)$ is the maximal number of the interest nodes in each row of sparse binary matrix. In the worst-case scenario, the time complexity is $O(MN^3)$. We conduct the experiments in random uniform layouts of sensor nodes to verify the effectiveness of MA-Greedy algorithm. The experiment results show MA-Greedy algorithm can improve the balance of energy consumption. What's more, the results of reconstructing sparse zero-one signals by sparse binary matrix are better than that by Gaussian random matrix.

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