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Energy-balanced compressive data gathering in Wireless Sensor Networks

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A B S T R A C T

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 is 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 algorithm), 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.

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 are not 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 computational 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 does not need to keep

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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 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. 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 does not 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. The notations in the paper are summarized in Table 1.

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 $i(1\le i\le N)$
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
$\overline{E}$	The average energy consumption of WSNs
$\hat{x}$	The reconstruction signal of x
ε	Relative error

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 does not consider how to use CS in multi-hop communication.

For multi-hop networking scenarios, CS in conjunction with routing was exploited in Quer (2009), where random projections of sensed data were transmitted to sink node. Routing matrix was the measurement matrix where the coefficients were generated by the same pseudo-random number generator at sensor nodes. Unlike the contribution in Quer (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 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 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 Network (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.