Compressive Sensing Based Data Gathering in Wireless Sensor Networks with Transmit-only Nodes

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Abstract

In this paper, we employ compressive sensing (CS) to design a data gathering scheme for wireless sensor networks (WSNs) with transmit-only nodes, where plenty of transmit-only nodes are activated to perform the sensing task and their data are gathered at a sink center to monitor environment using the CS principle. Typically, in the research published methods based on CS and random channel access, authors have used measurement matrix to reconstruct with encouraging results. However, they are limited in processing WSNs with transmit-only nodes. To account for the packet loss that occurs due to collisions, we propose a new approach with dual-measurement matrix reconstruction that minimizes average reconstruction error at the sink center. Simulation results demonstrate that compared with the conventional random channel access models, the proposed dual-measurement matrix model can improved reconstruction performance, and it is more effective in processing compressive WSNs with transmit-only nodes.

Key words: Compressive Sensing, Wireless Sensor Networks, Measurement Matrix, Transmit-only Nodes

1. INTRODUCTION

Wireless sensor networks (WSNs) (Yick et al., 2008; Hua et al., 2016; Xie et al., 2016) have been widely deployed for various purposes, such as environmental monitoring, disaster relief, and industrial automation. Hybrid wireless sensor networks (WSNs) with transmit-only nodes can effectively reduce network deployment costs, prolong the lifetime of the networks (Chuangeng et al., 2016; Zhao et al., 2013; Blaszczyszyn et al., 2008). Transmit-only nodes remove unnecessary receiving circuit, and therefore their communication cannot be coordinated. These nodes just transmit sensing data in a periodic or random way during work time. The packet loss that occurs due to collisions is severely limited in WSNs with transmit-only nodes, hence reducing collisions loss is of particular importance. Compressive sensing (CS) (Donoho, 2006) is a sampling paradigm that takes advantage of the sparse characteristic of the natural physical signals of interest, and makes it possible to recover signals with a small number of random measurements. Compression schemes for WSNs have been proposed (Baloucheanast et al., 2012;Xuet al., 2015), authors are more interested in energy, bandwidth, and tradeoffs than reducing collisions loss. Fazel (Fazel et al., 2011) employed Random Access Compressed Sensing to reducing collisions loss, however, reconstructed results using a random subset of sensor nodes, which will causes instability. Therefore, we present a new dual-measurement matrix consists of two different measurement matrix.

In this paper, we consider a static area network, where plenty of transmit-only nodes are deployed for long periods of time. Each sensor node communicates its observations of the field to a sink center, and the sink centerreconstructs the map of the physical field. The proposed method, based on compressed sensing and random access, compressive sensing provides a fresh perspective for efficient data acquisition without compromising data recovery. It enables a sink center to reconstruct the physical phenomenon with a reduced amount of data, where knowledge of the characteristics of the data is exploited. This inspired us to propose a new data gathering scheme for wireless sensor networks with transmit-only nodes. The system functions consist of three steps. Firstly, transmit-only nodes perform measurements, followed by a channel access method, during which measurements are transmitted to the sink center; finally, a reconstruction process, during which sparse recovery algorithms are used to recover the measured field at the sink center. In the sampling procedure,
inspired by the theory of compressed sensing, we employ random sensing. Since the transmit-only nodes just transmit sensing data, their communication cannot be coordinated. The data packets of two or more sensors may collide at the sink center. The key idea is that random collisions are inevitable. Due to both random sensing and losses due to random access, the sink center obtains an incomplete set of measurements. In order to achieve successful reconstruction, we present a new dual-measurement matrix consists of two different measurement matrices.

2. RELATED WORKS

2.1. Compressive Sensing

CS finds a sparse solution of an ill-posed inverse problem when the signal of interest is known to be sparse and compressible. A signal \( x = (x_1, x_2, \ldots, x_N) \in \mathbb{R}^N \) is defined to be \( k \)-sparse if it has a sparse representation in a proper \( B \in \mathbb{R}^{N \times N} \), where \( x = Bs \), \( s \) has only \( k \) non-zero elements. Based on the CS paradigm, compressed measurements instead of periodic signal samples are directly acquired. Random measurements \( y = (y_1, y_2, \ldots, y_M)^T \in \mathbb{R}^M \), where \( M \ll N \). The random measurements are generated by

\[
y = \phi x (1)
\]

where \( \phi = (\phi_1, \phi_2, \ldots, \phi_M)^T \in \mathbb{R}^{M \times N} \) is called the measurement matrix and is often a dense Gaussian matrix or a sparse binary matrix (Berinde et al., 2008). We have

\[
y = \phi x = \phi Bs (2)
\]

where \( \phi B \) satisfies the Restricted Isometry Property (RIP) (Baraniuk et al., 2008). It has been shown that we can reconstruct a \( k \)-sparse signal with high probability from only \( M = O(k \log(N/K)) \). CS measurements (Haupt et al., 2008) employing the following \( \ell_1 \) optimization problem (Donoho et al., 2006).

\[
\hat{s} = \underset{s}{\arg \min} \| s \|_1 \text{ s.t. } y = \phi Bs (3)
\]

Where \( \| s \|_1 = \sum_{i=1}^{n} |s_i| \), solving above problems is generally NP-hard. Some effective pursuit methods, such as Orthogonal Matching Pursuit (OMP) (Mallat et al., 2006) and Basis Pursuit (BP) (Tropp et al., 2004) have been proposed to solve this problem. In this paper, the \( \ell_1 \) optimization problem can be solved with linear programming techniques such as Basis Pursuit (BP).

2.2. Measurement Matrices

Consider a network of transmit-only nodes, we are interested in the measurement matrix. Up to now, a lot of measurement matrix have been proposed. Examples include Gaussian Matrix, Bernoulli matrix, sparse matrix, and so on. All non-zero entries of \( \phi \) represent the random Gaussian coefficients generated by the sensors which are sampled. Measurement Matrices satisfy the Restricted Isometry Property (RIP).

3 SYSTEM MODEL AND SCHEME

3.1. System Model

We consider a set of transmit-only sensor nodes with number of \( N \), deployed uniformly in a grid network shown in the Figure 1. Each node number \( n_i \). The network is deployed to monitor a physical phenomenon, (e.g., temperature, pressure, etc.) over a long period of time. The sink is placed in the center of the monitoring area. The measurements are encoded into a data packet, along with the measurement’s sequence, which is then modulated and transmitted to the sink from sensor nodes. The sink demodulates the signal and extracts the measurement information and sequence from which it reconstructs the map of the field. For the data gathering, we assume that the monitoring application is delay-tolerant.
3.2. Dual-Measurement Matrix Scheme

When the data is sent to the sink node, it first can be compressed through measurement matrix according to the requirement of the compressed sensing theory. Let us assume that sensor node \( n_i \) collect the data \( x_i \) in a period of time. The data transmit to sink is \( y_i = \phi x_i \). Where \( \phi \) is a measurement matrix. When the data \( y_i \) are transmitted to the sink node, some data is lost due to the collision, which is equivalent to the data transmitted to the sink through a random select measurement matrix. The data sink received is \( y_i' = \phi' y_i \), where \( \phi \) is a random select measurement matrix. That is \( y_i' = \phi' x_i \). This mean the actually measurement matrix in this data gathering process is \( \phi' \), and this matrix in referred as dual-measurement matrix in this paper. It is clear to see that dual-measurement matrix is satisfy the Restricted Isometry Property.

4. SIMULATION
4.1. Simulation Environment

In the simulation, we adopted synthetic signal model from literature (Zordan et al., 2011), which has been validated against real signals and allows the generation of time-varying spatial fields with tunable correlation characteristics. This is especially useful to control the degree of correlation in space and time and numerically assess its impact on the performance of the selected compression schemes. In the Figure 2, we show 10 single time instant for two synthetic signals generated with this model. Left curve in the figure is low temporal correlation and right is high temporal correlation.

The topology used in simulation experiment show in figure 2, transmit-only sensor nodes transmit data packets to sink directly in a random access way. Every data packet contains 8 protocol bytes and 2 data bytes and the data rate is 250Kbps.
4.2. Simulation Results

We compare three different measurement matrices, Gaussian matrix, Bernulli matrix, and Random matrix. Random matrix is like RACS which is mentioned in literature (Fazel et al., 2011) and it selects a subset nodes from sensor nodes in a random way. In order to test the performance of dual-measurement matrix under different compression ratio, we test the test data of six different data compression ratio in the experiment, and compression ratio $a$ is from 0 to 0.5.

![Graphs showing the comparison of Gaussian, Random, and Bernulli matrices for different compression ratios.](image)

**Figure 3.** Low temporal correlation

![Graphs showing the comparison of Gaussian, Random, and Bernulli matrices for different compression ratios.](image)

**Figure 4.** High temporal correlation
The Figure 3 is the reconstruction error of low temporal correlation data. From our experiment data, we find that random matrix’s reconstruction error is unstable. When the measurement matrix is the Gauss and Bernoulli matrix, the reconstruction error is more stable. It can be seen from the experiment that the performance of the Gauss matrix is close to that of Bernoulli.

The Figure 4 is the reconstruction error of high temporal correlation data. Compared with low temporal correlation data results, the whole reconstruction error is smaller. It can be seen that with the increase of the compression rate, the error of the random matrix is more and more unstable. Compared to the random matrix, the reconstruction error jitter of Gauss and Bernoulli matrix is small.

5.CONCLUSIONS

This paper discusses the application of compressed sensing technology in wireless sensor networks with transmit-only nodes. We propose a dual-measurement matrix algorithm, before transmitting the data to the sink node, sensor nodes compress the data through measurement matrix. During the transmitting, loss of the data is equivalent to compress by the random measurement matrix. Through the simulation experiment, the Gauss measurement matrix and Bernoulli measurement matrix can get a more stable reconstruction error than using the random matrix.

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