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Effective Compressive Sensing for Clustering in Wireless Sensor Networks

Gaurav Kumar Nigam* and Chetna Dabas

Department of Computer Science and Engineering, Jaypee Institute of Information Technology, Noida - 201301, Uttar Pradesh, India; gaurav.nigam@jiit.ac.in, chetna.dabas@jiit.ac.in

Abstract

Wireless sensor Networks consists of a huge number of little powered nodes typically in the range of hundreds to thousands in number that are multifunctional and randomly deployed in a hostile environment. If a node detects an abnormal event, it will automatically send a hop by hop warning message to the sink node. There are various challenges and design issues in WSN like node deployment, routing, energy consumption, clustering, fault tolerance, coverage, connectivity and QoS i.e. Quality of Service. The author proposed a clustering approach that adopts a hybrid Compressive Sensing (CS) for sensor networks. The method compares the number of transmissions in the data aggregation techniques commonly used: Shortest path tree with hybrid compressive sensing, clustering without compressive sensing, optimal tree with hybrid compressive sensing, shortest path tree without compressive sensing, clustering with hybrid compressive sensing. Compressive sensing uses the largely similar data of large scale Wireless sensor networks and aims to minimize data transmissions without compromising the precision of the result obtained from data. The author finds that in comparison to these methods the proposed approach can reduce the data transmissions.

Keywords: Cluster Head, Compressive Sensing, Shortest Path Tree, Wireless Sensor Networks

1. Introduction

Wireless sensor networks are sensors distributed across space to observe physical as well as various environmental surroundings viz. pressure temperature and sound and so on. Sensors pass on the sensed data through the network. WSN is built of "nodes", where each node has a radio transceiver with an attached antenna, some source of energy, a microcontroller and a circuit. In computer science and wireless communications, WSN is a live researching domain[4,5]. The base station (BHs) nodes are considered as a node with higher processing and computational potential than normal nodes. They provide a portal between sensor nodes and an end by typically forwarding data from the wireless sensor networks on to a server. Sensors are usually thrown from an aircraft or plane into a geographical region that wish to be monitored and that is distributed uniformly[26]. Sensors typically work in severe surroundings where it is not possible to provide any preservation or resupply of power. They run on their battery provided on-board and they will send the data until their battery power runs out. In this paper, the author has worked on the clustering problems that will save the energy for WSNs[18,19].

We can say that the traditional sampling approach is not energy efficient as it will contain a bulk amount of extravagant information about the transmitted data[1–3]. An alternative approach[2] that is generally used to overcome this is compressing and transmitting. In spite of reduction of power consumption in transmission; compression wishes extra energy and appeal computational power from available sensor nodes. Compressive sensing uses the correlation in the data of large scale WSN networks and aims to minimize data transmissions without compromising the precision of the result obtained from data[9,11].

Compressed Sensing (CS) is considered as signal processing approach that is used for regenerating and

**Author for correspondence*

achieving a signal. In spite of traditional methods, CS reveals that one should be able to regain assertive signals and images from lesser number of available samples. CS is a detailed protocol that is used for simultaneously sensing and compressing the data and is named as 'compressive sensing'. It follows via the principle of maximization; the sparse nature of the signal can be overburdened to regain it from distant petty available samples than the desired one. There are two conditions that make sparsity possible[10,12]. One of them is sparsity which is possible when the signal is sparse in some domain. The second characteristic of a signal that makes recovery possible is incoherence that is related to the isometric property which is tolerable for sparse signals. As a result of compressive sensing the 'information bandwidth' is less than total bandwidth, hence it becomes possible to sample below Nyquist without information loss, recover missing samples by convex optimisation and it also saves precious bandwidth.

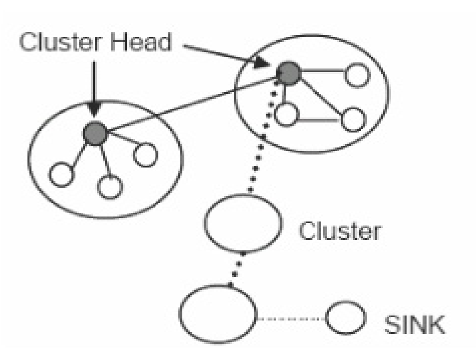

Figure 1. Clustering in wireless sensor network.

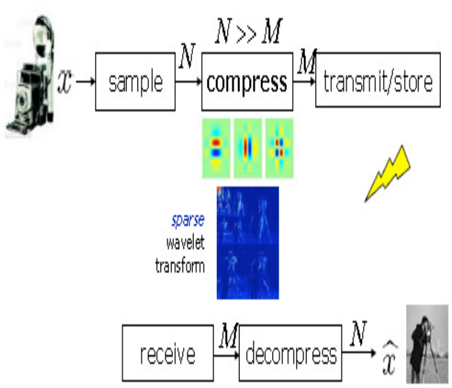

Figure 2. Diagram illustrating compressive sensing.

The present paper deals with proposing a clustering method that make use of hybrid CS. The balance of the paper is labelled as Section 2 that contains mathematical formulation of compressive sensing. Section 3 portrays the problem formulation path. In Section 4, implementation is given and finally conclusion is given in section 5.

2. Mathematical Formulation

We are required to regenerate a signal from a set of consistent data in case of image and signal processing. The problem formulation condensed to a set of linear equations. In terms of mathematics, we say that the checked data $y \in C^m$ is associated to the signal $x \in ₵^N$ of concern via

$$\mathbf{A}x = y. \quad \ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Here, matrix $\mathbf{A} \in ₵^{m\times N}$ formulates the process of linear measurement[6]. By solving the eqn (1), one could find the vector $x \in C^N$. Here, m is defined as total number of measurements and its value is taken to be atleast larger than length of signal N[13]. This is the basic idea that is applicable in case of mostly used current devices like conversion from analog-to-digital, radar, and mobile technology, medical imaging. if value of m<N, then the theory of classical linear algebra validates that the system defined in (1) is underdetermined and should consist of many infinite solutions[6].

If the value (m<N), we can recover the value x from y. This is also related to Shannon sampling theorem that tells that the rate of sampling of a time signal that is continuous should be twice the value of its highest frequency to validate reconstruction. It is achievable to regenerate signals if m<N and there are various efficient algorithms that exists for reconstruction. Sparcity makes the underlying assumption possible[6]. The area of research that is related to this term is called as compressive sensing. Problems related to Compressive sensing should consist of regeneration of a sparse vector i.e. $x \in ₵^N$ from the assessments:

$$y = Ax \in ₵^m, \text{ if } m<N \;\; \ldots\ldots\ldots (2)$$

3. Approach to Problem

We can say that the traditional sampling approach is not energy competent as it will contain a bulk amount of extravagant information about the transmitted data[7]. Thus, compressive sensing seems like a smart way to minimize the overall statistic of transmissions in large scale WSN's as compressive sensing enables us to acquire just the useful part of the data and reduces the overall redundancy of data[8]. The proposed approach using hybrid compressive sensing is used to minimize the number of transmissions in sensor networks. The sensor nodes are formed into group of clusters. When we talk about inside a cluster then nodes can broadcast data to Cluster Head (CH) beyond employing compressive sensing. Cluster heads adopt compressive sensing to broadcast data to sink[20,21].

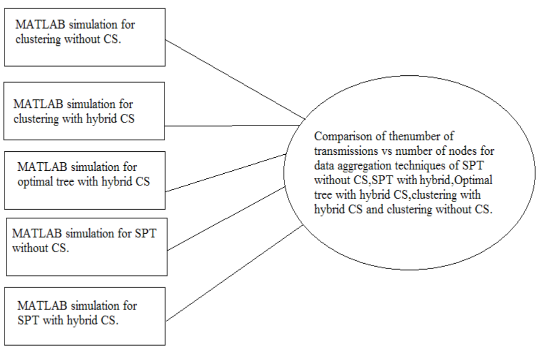

Figure 3. The architecture of the data aggregation protocol simulation

The basic idea behind the current work is a clustering algorithm using compressive sensing that is used in wireless sensor networks for efficient data aggregation[16–18]. The author proposed a clustering approach that adopts hybrid CS for sensor networks. The nodes are formulated into clusters and inside a cluster the nodes deliver data to a CH beyond adopting compressive sensing. Cluster heads adopt CS in order to convey data to sink. During each round, the CS projections are added together at CHs. After the sink receiving information about all available rounds of projections, we may able to recover the original data of all sensors. Finally, we correlate the number of transmissions in order to compare different methods. The proposed hybrid method using CS can curtail the number of communications in sensor networks. This is novelty of current work as this will drastically minimize the number of transmissions, as compared to other data aggregation techniques.

In Table 1, comparison of shortest path tree and cluster that are used during routing[14] to provide data aggregation in wireless sensor networks is given.

Table 1. Comparison of shortest path tree and clustering in WSN routing

Shortest path tree (SPT)	Clustering in data aggregation
This approach is tree-based. It normally bet on hierarchical grouping of nodes. It will compose a tree structure by employing a very simple strategy. Information of every source is sent to the sink via the shortest path where there is an overlap for different sources. Thereby, they are united to construct the aggregation tree. It has static routes.	It is a cluster-based approach. The Cluster head acts as the aggregation point. It aims at maximizing the overlapping routes for data transfer and reducing the communication cost.

4. Implementation

The paper evaluates the reduction ratio of CS cluster compared with three traditional methods clustering without CS, Shortest Path Tree (SPT) without CS, and SPT with hybrid CS. Table 2 consists of the requirement parameters for the simulation of the data aggregation techniques.

Table 2. Requirement specification

PARAMETERS	VALUES
Network size	20m X 10m
Location of sink	(0, 0)
Density of nodes	2-6
Number of nodes	400-1200
Transmission range	√2 unit
Edge length	1 unit
Compressive ratio	5-10

Firstly, A MATLAB code will be designed to evaluate the contraction proportion of transmissions of CS cluster that is correlated to three traditional methods: clustering without CS, SPT without CS, and SPT with hybrid CS.

Secondly, we analyze the transmission ratio in each case and evaluate the results. The solution is designed keeping in mind the maximum possible accuracy rate that can be achieved with the parameters used in the simulation.

The author uses the number of transmissions in order to compare his method with other methods. It is found that the number of communications of proposed approach is somewhat shorter than that of the clustering method that doesn't uses compressive sensing. We can say that the number of transmissions of our approach is apparently lower in comparison to SPT with hybrid CS whereas it is marginally larger when compared to the optimal tree with hybrid CS.

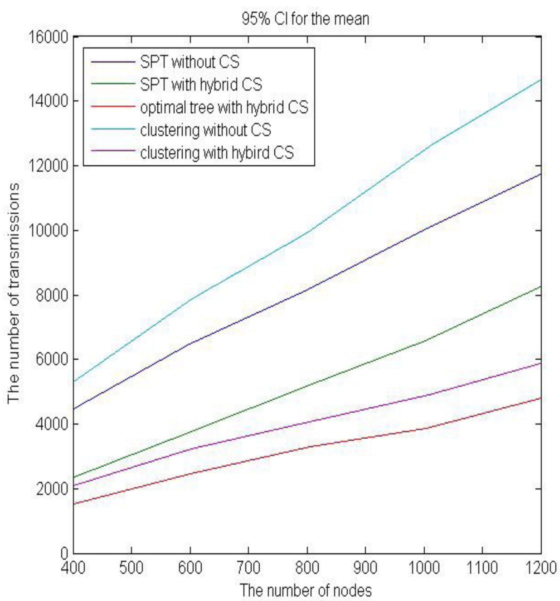

Figure 4. Study of no. of comparisons for the methods considered when compressive ratio is 10.

Figure 4 shows comparison among our approach with other methods in terms of reduction ratio of transmissions. If the value of compressive proportion is agreed to ten, it is seen that our method reduces about sixty percent the total number of transmissions when it is compared to clustering without CS whereas total the number of transmissions is reduced to about fifty percent when it is correlated with SPT without CS. If the number of nodes is agreed to 1,200, it is realized that the overall transmissions is reduced to about thirty percent when we correlated it with SPT with hybrid CS. It is also seen the reduction ratio doesn't fall even if we raise the number of nodes. It illustrates that proposed approach is scalable and is used easily in case of large-scale networks.

Figure 5 illustrates, if compressive proportion is five, the reduction ratio of the proposed method contracts to around ten percent when we correlated it with the scenario when we agreed the compressive proportion to ten. It proves that the proposed approach has convincing advancements in the unfavourable scenario.

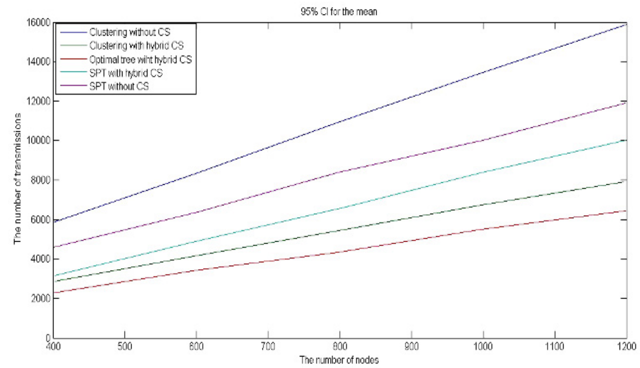

Figure 5. Study of no. of comparisons for the methods considered when compressive ratio is 5

5. Conclusion

The author used hybrid CS in order to compose a clustering-based data compilation method that will minimize data transmissions in wireless sensor networks. CHs can collate the data within a cluster via shortest path routing. Data are restricted to the projections via CS method at CHs. A backbone tree structure is formed when the projections are delivered to the sink. The proposed method can minimize to nearly thirty percent the number of transmissions, when it is correlated among other available data selection method that make use of SPT with hybrid CS. In case of non homogenous networks that work in an uneven sensor field, it is found that proposed approach can convincingly minimize data transmissions correlated among other data selection methods.

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