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A Review of Compressive Sensing (CS) Scheme in Cluster based Wireless Sensor Networks

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Abstract

Wireless sensor network has become one of the most interesting and emerging areas of research in the past decade. Recent advances in technologies have increased the use of wireless sensor networks in different applications like chemical and physical monitoring, healthcare, tracking and soon. Most of the applications of a wireless sensor network, a huge amount of data is processed which consumes more energy. The compressive sensing scheme is a growing technique in a wireless sensor network used to reduce the number transmissions and to reduce the amount of data to be processed and also for effective utilization of limited energy radio resources. This paper presents various types of compressive sensing techniques used in a wireless sensor network.

Keywords: compressive Sensing, data aggregation, clustering, wireless sensor network (WSN)

INTRODUCTION

In WSN, sensor nodes are equipped with competence of sensing various kinds of physical and environmental conditions, data processing, and wireless communication. The most critical applications of the Wireless sensor network rely mostly on the accuracy and availability of target's location such as disaster response, vehicle tracking, and geographical routing, Global positioning system [25]. The large-scale wireless sensor network consumes a significant amount of energy through data transmission. In order to maximize the network lifetime significantly as well as to minimize the overall energy consumption, the load must be evenly distributed and the in-network communication must be reduced completely. Employing low power sensor and energy efficient algorithm on the physical layer and other methods will improve the lifetime of the sensor as well as decreases the energy consumption in many network layers [26]. The clustering method can be used to design hierarchical energy efficient sensor network in order to achieve a reliable data transmission, load balancing criteria and scalability [27]. Energy consumption for data transmissions during sending and receiving is the most important factor considered in WSNs. Different methods have been proposed to achieve for compression of data including traditional source coding and distributed source coding. In WSN environment, the sensor nodes collect information about the environmental parameters such as temperature, pressure, humidity, pollutants, vibration, and movement to monitor the real-world phenomenon [39]. Energy consumption is a crucial performance parameter to evaluate the life time and throughput of wireless sensor network because the sensor nodes are operated with battery with limited energy [40]. Compressed sensing technique presents a new sampling scheme to minimize the transmitted data in order to decrease power consumption in WSNs. Compressive sensing concept is a new idea in signal processing field to achieve good signal reconstruction with reduced sampling rate for sparse signals such as signal vector from large number sensor measurements in WSNs. In large-scale sensor network applications, there exists a temporal or spatial correlation of data from multiple sources and signals can be sparse in nature in a known orthogonal basis function, so the compressed sensing technique can be effectively applied to wireless sensor networks. Compressive sensing can be used to reconstruct the signal in WSN from a small number of linear measurements.

COMPRESSIVE SENSING OVERVIEW

Wireless sensor network operates based on the three fundamental operations: sensing, data processing, and data communication. These are the major power hungry parameters in WSNs. Generally, energy consumption for data communication operation is more compared to that of sensing and data processing. In WSN, there is a possibility of node failures due to the limited battery power so that the lifetime of wireless sensor network will decrease. The lifetime of wireless sensor network can be increased if we can reduce the number of transmissions in the network. Thus, reducing the total energy consumption is very important in the design of WSNs [3]. Many researchers have addressed the challenges of energy efficiency in WSN to increase its lifetime through different methods like sleep scheduling of nodes [22], topology control [21], and data aggregation [4]. To increase the network's life time and energy efficiency implementation of proper data aggregation and touting techniques are needed in WSNs. In a real-world WSN, the sensed data has spatial correlation properties; hence the compression techniques can be used to reduce the number of data transmissions with high recovery accuracy in the sink node. This spatial correlation property leads to an incoherent sparsity of sensed data in a known basis such as wavelet domain or discrete cosine transform [20].

Compressive sensing claims that a signal can be recovered from a small number of projections onto a second basis if it has a sparse representation in one basis. So, a sparse signal can be recovered from a very few samples. Such capability of compressive sensing brings the benefits of reduced transmission bandwidth and storage requirement due to the compression achieved. Compressive sensing can be used to reconstruct the sparse signal which is compressible from a small number of linear measurements without having knowledge about the signal structure in priori which is the major strength of the CS algorithm. Compressive sensing is needed in WSN applications where the measurements are expensive, and computations at the receiver end are cheap [1]. Compared with data compression, implementation of compressive sensing in WSN brings a promising improvement because the low powered sensor nodes are not capable of handling encoding of data compression methods [2].

A. COMPRESSIVE SENSING MODEL

Let $x \in \mathbb{R}^n$ be a sparse signal vector and $y \in \mathbb{R}^m$ be a compressed signal vector (m<<n), the linear measurements of x is given by

$$y = \phi x = \phi \psi S \qquad (1)$$

Where ϕ is a measurement matrix (or sensing matrix) of size $m \times n$, ψ is a transformation basis of size 'n' and S is a k-sparse representation of x.

Reconstruction of x from y can be possible with few measurements [29][30] by solving an optimization problem through l_1 norm minimization given by

$$\min_x \|x\|_1 \text{ such that } y = \phi x \qquad (2)$$

The necessary condition for recovering x from the linear measurements y is that the matrix ϕ must satisfy the Restricted Isometry Property of order k given by

$$1 - \delta \le \frac{\|\phi u\|_2}{\|u\|_2} \le 1 + \delta \qquad (3)$$

Where u is a vector with k-non zero entries and $\delta > 0$ is known as restricted isometry constant [31]. Another condition to satisfy stability is that the measurement matrix ϕ must be incoherent with the sparse basis ψ and the vectors $\{\phi_i\}$ cannot sparsely represent the vectors $\{\psi_i\}$ and vice versa [29,30,32].

Extensive research work has been made to develop various sparse signal reconstruction algorithms [33], in which one group of commonly used algorithms are convex relaxing based algorithms like Basic Pursuit (BP), Dantzig Selector etc.; another group of algorithms is greedy pursuit algorithms like Matching Pursuit, Orthogonal Matching Pursuit, Stagewise OMP, Subspace Pursuit etc. Both types of techniques have advantages and disadvantages when applied to different applications.

COMPRESSIVE SENSING USAGE IN WSN

A wireless sensor network consists of spatially distributed sensor nodes, where each node has the capability of sensing, processing, and communicating the data. In a normal sensor network, all sensor nodes transfer the sensed data to the base station, which performs the final data aggregation and extraction tasks [5]. A wireless sensor network consists of 'n' nodes, each having the data x_j, j= 1, 2, 3….n. and the scalar value of each sensor node in WSN is represented in x_j, so that the sensor network data is represented in a signal vector form as given by [12]

$$x = [x_1, x_2, x_3 \ldots\ldots x_n]T.$$

In a traditional sensor network without CS technique, the network needs to acquire all 'n' samples of the signal 'x' to complete the group of transform coefficients. Since the data vector x is very large, the WSN need to process a huge amount of data with thousands of nodes. Suppose if x has a k-sparse representation in known basis $\psi = [\psi_1, \psi_2, \psi_3 \ldots\ldots \psi_k]^T$, then the data vector can be represented by [39]

$$x = \sum_{j=1}^{N} S_j \psi_j$$

Wireless sensor network with compressive sensing can reduce the information in data from 'n' to 'm' and transmit only 'm' data which saves memory and energy consumption. Instead of x, WSN can collect compressible data vector y such that there exists a stable information sensing matrix ϕ. The compressive data gathering in wireless sensor networks is as shown in the fig. 1. Instead of receiving individual sensor reading, from all sensor reading, 'm' weighted sums will send to a sink which reconstructs the data from these measurements [34]. In a wireless sensor network, data is communicated from the source node to sink node through a multi-hop transmission. Initially, the source node data is communicated to the next neighbor as weighted sensing matrices and at the next neighbor, the data is collected as a weighted sum of the previous sensor reading. Finally, at the sink node, the aggregated data of 'm' weighted sums of sensor data is received as shown in the figure below.

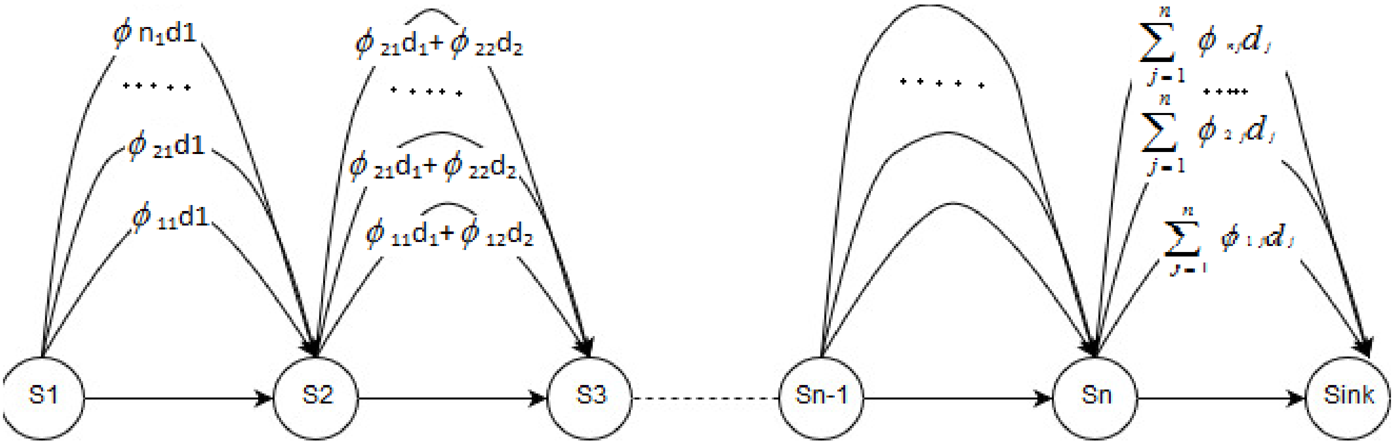

Figure 1. Compressive data gathering in wireless sensor networks (adapted from [34]).

REVIEW OF LITERATURE

In the past few decades, the researchers have been focused on wireless sensor networks with data aggregation methods using compressive sensing in order to increase the lifetime of WSN by reducing the number of data transmissions and balancing the traffic load [35]. The Literature survey is based on hierarchical compressive sensing in cluster-based wireless sensor networks, where both are challenging as well as interesting topic and it has been receiving some increased attention.

Compressive data gathering by using the random projection: [38] proposed a compressive data gathering by using the random projection for energy efficient wireless sensor networks. The compressive data gathering is employed to improve the energy efficiency of the wireless sensor network as well as attributing to the data compression. The MST projection generate a minimum number of spanning trees that are routed at randomly selected projection node to aggregate the sensed data from the nodes by employing the compressive sensing [38]. This method can be further developed by joining sink node to the spanning tree and making the root of the spanning tree as the sink node.

Compressive sensing based target counting: In wireless sensor network applications like target counting and positioning, compressive sensing has been applied for these applications in [8][9]. To estimate the locations of sparse events, J. Meng et al. [8] propose a Bayesian detection algorithm by considering a binary event model in wireless sensor networks. Chen Feng et al. [9] propose a multi-target localization to find the locations of objects in which they used a small number of measurements of received signal strengths to find the locations of targets. Also, they introduced a pre-processing procedure on original measured data and to compensate for the spatial discretization due to the grid assumption, a post-processing procedure is used. In [28], authors provide a rigorous proof for the applicability of compressive sensing theory in target counting and localization. Also, they showed that and in target counting/positioning applications, the Greedy Matching Pursuit (GMP) algorithm gives high accuracy. A target counting error (COE) and the localization error or position error (LOCE) can be expressed as:

$$COE = \frac{\sum_{j=1}^{N} |n_j - \hat{n}_j|}{\sum_{j=1}^{N} n_j}$$

Where n_j denotes actual number of targets and $\hat{n}_j$ indicates the estimated number of targets.

$$\text{LOCE} = \frac{\sum_{j=1}^{n_{min}} \sqrt{(x_j - x'_j)^2 + (y_j - y'_j)^2}}{r.n_{min}}$$

where (x_n, y_n) indicates the actual locations of the targets for n = 1, . . . , k ; (x'_{ne}, y'_{ne}), represents estimated locations of the targets for ne = 1, . . . , k; n_{min} = min {n, ne} and r is the grid size. The greedy matching pursuit algorithm provides less counting and positioning errors compared to other CS reconstruction algorithms [28].

Adaptive compressive sensing: The authors [12] propose an adaptive compressive sensing based adaptive algorithm for information collection in wireless sensor networks. For an energy efficient way of information collection, this algorithm performs projections iteratively to maximize the information gain per energy expenditure. However, they proved that the calculation of projection vector in adaptive compressive sensing is an NP-hard optimization problem, which brings high overhead. To solve this optimization problem, they provide a number of heuristics with increased complexity. Jun Luo et al. [13] propose the way of improvement of throughput in a wireless sensor network by applying compressive sensing as an in-network data aggregation scheme. They compute the throughput of non-compressive sensing and plain-compressive sensing schemes and designed a hybrid-compressive sensing scheme that combines both plain-CS and conventional data collection to improve performance. In [19], compressive sensing is applied in a multi-hop wireless sensor network. Energy consumption can be reduced by applying compressive sensing in multi-hop sensor network through joint routing and compressed data aggregation. Also, they proved its NP-completeness of the optimization problem.

Non-uniform Compressive Sensing (NCS) method: [15] proposed a non-uniform compressive sensing method based on the two basic characteristics compressible nature of physical phenomenon and heterogeneity of wireless sensor network. The authors evaluated the NCS with a real data points in WSN application and proposed a distributed implementation of NCS for energy-aware communication applications. This method introduces very little communication, signal approximation accuracy with fewer samples compared with previous methods.

Compressive Data Gathering (CDG) with multi-hop transmission, Chang Luo et al.[16] presented a compressive data gathering scheme for large-scale wireless sensor networks. The network capacity is increased proportionally to the sparsity of sensor readings. They also consider the design of measurement matrix ø and ψ from both compressive sensing and communication aspects. Also, they generate Restricted Isometry Property preserving sensor readings by taking multi-hop communication cost into account. The proposed CDG, various sparsity patterns can be utilized.

Hybrid Compressive Sensing: In [17], authors proposed a hybrid compressive sensing for data collection in a clustering based wireless sensor networks in order to reduce the number of data transmissions. In this, sensor nodes are organized into a cluster. Within a cluster, sensor nodes communicate the data to the cluster head directly and the cluster heads transmit the data to the sink using compressive sensing. The sensor nodes within the cluster transmit their data to cluster head through shortest path routing.

Total number transmissions within a cluster in the WSN is given by

$$\left(\frac{D^3-D}{3}+D^2\right).\lambda a^2.\frac{N}{\lambda D^2 a^2}=\left(\frac{D}{3}-\frac{1}{3D}+1\right).N=T_{intra}$$

Total number of transmissions between clusters with compressive sensing for M rounds is given by

$$T_{inter}=\frac{NM}{\lambda a^2}.\frac{1}{D}-\frac{M}{2}.D$$

Total number of transmissions in the hybrid CS is T= T_{intra}+ T_{inter}.

The optimal cluster size is, $N_c^* = \lambda(D.a)^2 = \begin{cases} \frac{3M-\lambda a^2}{1-\frac{3M}{2N}},\ M<\frac{2}{9}N; \\ N,\ \frac{2}{9}N \le M \le N. \end{cases}$

In this proposed method, the total number of transmissions using hybrid compressive sensing in cluster-based WSN is minimized.

Compressive sensing conjugate gradient based reconstruction algorithm: to remove the need of choosing sparsity weightings priori, the authors [18] proposed a compressive sensing based reconstruction algorithm with conjugate gradients using a multilevel sparsity reduction method. In this reconstruction process, the effect of noise on reconstruction accuracy is analyzed using different simulations. From the experimental measurements of XPM-2 Phantom Mouse using compressive sensing and reconstruction, they showed that the performance of CS-based reconstruction algorithm is superior compared with traditional reconstruction methods in the presence of noise.

Cluster-based weighted compressive data aggregation: In a conventional compressive sampling (CS) method, involving more number of sensor nodes for each compressive sensing measurement lead to insufficient energy consumption in a wireless sensor network. The weighted compressive data aggregation [27] is introduced as a new technique in networking layer to benefit from the sparse random measurement matrix for the reduction in energy consumption. This algorithm implies a unique power control capacity in the sensor node to have an energy efficient routing tree to reduce the issues with load balancing and the cluster-based WCDA is imposed to decrease the power consumption in WSN model. The number of sensors that are involved in CS measurement in the cluster can significantly reduced by implying the WCDA algorithm. The load balancing, energy consumption and other lifetime perspectives of the network are evaluated with respect to the effectiveness of this proposed algorithm.

Clustered Spatio-temporal coding with CS: Chen et al. (2016) developed a clustered Spatio-temporal coding by integrating the compressed sensing, network coding and spatio- temporal compression of the correlated sensor data readings in the Wireless sensor network [36]. The reconstruction of original data with high probability has been successful with the deployment of NC and CS in real WSN fields. This scheme reduces the reconstruction error with the use of encoding technique independently to all sensor nodes including the cluster head nodes. At the sink node, they are decoded in to reduce the complexity. Moreover, to further optimize this model, an iterative distributed algorithm is used to reduce the reconstruction error.

Energy efficient distributed compressed data gathering: Wang et al. (2017) proposed a novel model for compressed data collection for wireless sensor network based on distributed CS theory [37]. The quantization configuration is also a critical factor for energy efficiency for data communication. The enabling of sub-Nyquist sampling rate has reduced the energy cost and the compressive sensing is more attracted because of this approach. The quantization configuration is a critical factor for energy efficiency for data communication that constructs the energy consumption configuration model for the joint distribution compressive sensing and quantization compressive sensing.

A. GAPS IDENTIFIED IN THE LITERATURE

The sink node, instead of receiving each sensor's reading by one packet in a multi-hop route is based on Compressive sensing technique that receives only a few weighted sums from all the nodes in the network by gathering the weighted nodes readings on their routes path from the leaf nodes to the sink [38]. Moreover, using more number of nodes for each compressive Sensing measurement leads to more power consumption in WSN. The overall transmission cost and distribute the traffic load more evenly throughout the network has not been minimized. The self-determination of the nodes and self-activation of the nodes based on their signals strength have not been improved [36]. The enabling of sub-Nyquist sampling rate has reduced the energy cost for the data collection in data compressive theory can be improved [37].

Comparison of different compressive sensing techniques in wireless sensor networks is presented in Table 1.

Table 1 Comparison of existing methods

Ref	Author	Technique	Advantage	Disadvantage
13	J. Luo, L. Xiang, and C. Rosenberg	hybrid-CS scheme	Performance is improved	Traffic is larger
12	C. Chou, R. Rana, and W. Hu	adaptive compressive sensing	Maximizes information gain	Relatively high communication and computational overhead
9	C. Feng, S. Valaee, and Z. Tan	Greedy Matching Pursuit (GMP) algorithm	The target decay matrix satisfies RIP	Accuracy is high in target counting/ positioning.
10	Gaurav Kumar Nigam and ChetnaDabas	Hybrid CS for data aggregation	Minimizes the total number of transmissions in WSN	It does not conserve the flow at the aggregators.
18	Hector R. et al	Compressive sensing conjugate gradient based reconstruction algorithm.	Removed the need of choosing sparsity weightings priori using a multistage sparsity reduction approach	This method is not optimized for efficiency
17	Ruitao Xie and Xiaohua Jia	Hybrid compressive sensing in clustering based WSN	Number of data transmissions are reduced	Possibility of network coverage and connectivity problems.
15	YiranShen, et al.	Non-uniform compressive sensing (NCS) method	Network performance is improved	Accuracy in less energy consumption
16	C. Luo, F. Wu, J. Sun, and C. W. Chen	CDG with multi-hop transmission	removed the need for centralized controlling and complicated routing	limit the communication cost without jeopardizing the data recovery
27	Abbasi-Daresari, S. & Abouei, J.	Weighted compressive data aggregation in cluster-based WSN	Reduces energy consumption	Only random selector nodes are considered for the implementation

CONCLUSION

In large scale and cluster-based WSN, the existing compressive sensing based data aggregation schemes are not sufficient in terms of energy consumption and number of data transmissions in the network. In this paper; different types of compressive sensing techniques are presented. Even though some of these compressive techniques are still under development, but the experimental results indicate that their compression rate and reduction in energy consumption are quite impressive. Various methods are implemented to improve the performance of compressive sensing but a still inherent restriction of energy. It is important to minimize the drawbacks of existing techniques by improving the performance of compressive sensing techniques. Thus the integration of heterogeneous clustering approach in a wireless sensor network with hierarchical compressive sensing with novel algorithms is expected to achieve better data accuracy and efficiency in the WSN for data processing.

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