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Compressive Sensing In WSNS: A Review

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ABSTRACT:
In Wireless sensor networks (WSNs), compressive sensing (CS) provides a new paradigm for efficient data gathering. The CS requires capturing a small number of samples for successful reconstruction of sparse data. In this paper, we describe the literature survey of using CS technique in WSNs and then present the overview of this CS technique. This paper also highlights some of the reconstruction algorithms and finally presents its applications in networking domain.

Keywords: WSNs, Compressive sensing, Sparsity, Incoherence, Reconstruction, Applications

I. INTRODUCTION

WSNs typically consist of a large number of small, low-cost sensor nodes which are distributed over a large area. These sensor nodes are integrated with sensing, processing and wireless communication capabilities. The main task of a sensor node is to sense and collect data from a certain domain, process them and transmit it to the sink where the application lies as shown in fig.1. Each node is equipped with a wireless radio transceiver, a small microcontroller, a power source and multi-type sensors such as temperature, humidity, light, heat pressure, etc. WSN have great potential for many applications in scenarios [1] such as military target tracking and surveillance, natural disaster relief, biomedical health monitoring and hazardous environment exploration and seismic sensing.
Generally, the sensed physical data is transmitted from the sensor nodes to the sink node (or base station) through multi-hop routing [2].
Since the sensor nodes usually have limited computing ability and power supply, it is desirable to have simple and energy-efficient data gathering (or aggregation) method to reduce data transmission consumption of each sensor. In many situations, it is inefficient for sensors to transmit all the raw data to the sink, especially when sensed data exhibits high correlation. To reduce transport load, conventional compression techniques are usually used to exploit the correlation among sensor data so that less data can be delivered to the sink without sacrificing the salient information.

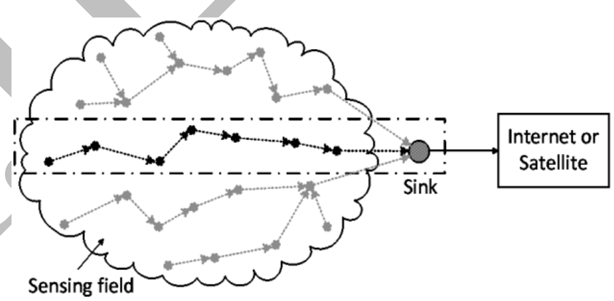

Fig. 1. Data gathering sensor network

In large-scale wireless sensor network, Compressed Sensing (also known as compressive sampling or CS) is a novel data compression technology to reduce global scale communication cost without introducing intensive computation or complicated transmission control[3]-[4]. This will result in extend the lifetime of the sensor network. CS theory asserts that one can recover certain signals and images from far fewer samples or measurements than traditional methods use. To make this possible, CS relies on two principles [4]: sparsity, which pertains to the signals of interest, and incoherence, which pertains to the sensing modality. CS combines the sampling and compression into one step by measuring minimum samples that contain maximum information about the signal: this eliminates the need to acquire and store large number of samples only to drop most of them because of their minimal value. This technology [14] is combined with the appropriate routing protocols to improve the communication capability to the entire network of the entire network, latency and network survivability life and other issues. Compressive sensing has seen major applications in diverse fields, ranging from image processing to gathering geophysics data.

CS provides an alternate to Shannon /Nyquist sampling [4] when the signal under consideration is known to be sparse or compressible. The Nyguist sampling theorem defined that the sampling rate must be at least twice the maximum frequency present in the signal. In traditional signal processing techniques, we uniformly sample data at Nyquist rate, prior to transmission, to generate 'n' samples. These samples are then compressed to 'm' samples; discarding n-m samples. At the receiver end, decompression of data takes place to retrieve 'n' samples from 'm' samples. The paradigm of Shannon's sampling theory is cumbersome when extended to the emerging wide-band signal systems

The rest of the paper is organised in the following manner: section II presents the literature survey of CS technique in WSNs. Section III presents the compressive sensing method and various reconstruction algorithms. Section IV presents the application of CS in networking domain and finally section V concludes this paper.

II. LIETRATURE SURVEY

In WSNs, CS techniques are used for various purposes such as data acquisition or data gathering, data transmission. In many research works, compressive measurements and data acquisition are one of the key issues and the field is witnessing significant advancement on a daily basis. This section mainly includes compressive measurements and data acquisition related works.

In [5], the authors present the first complete design to apply compressive sampling theory to sensor data gathering for large-scale wireless sensor networks. In this paper, the authors consider the scenario in which a large number of sensor nodes are densely deployed and sensor readings are spatially correlated. The basic idea of this method is that a spanning tree rooted at the base station will be generated, and the tree contains all the sensor nodes. Giving an M by N projection random matrix $\Phi M\times(M < N)$, each leaf node sends projection vector with length M to its parent node along the spanning tree. After receiving the projection vectors from all its children nodes, the intermediate nodes add the vectors and then send the result vector to its own parent node. In the end, the base station can recover all the original sensory data from the final projection vector. This proposed method is capable to extend the lifetime of the network. In [6], the author uses an intelligent compressive sensing for data gathering in WSN. For achieving efficient data gathering, the author introduces an autoregressive (AR) model into the reconstruction of the sensed data so that the local correlation in sensed data is exploited and thus local adaptive sparsity is achieved.

Xu et al. [8] proposed a hierarchical data aggregation using compressive sensing (HDACS) scheme to address the local sparsity instead of global sparsity. The proposed architecture is designed by setting up multiple types of clusters in different levels. In [7], the authors proposed a hybrid CS method. In this approach, each leaf node only needs to send its own single sensory data instead of projection vector to its parent node.

Cheng et al. proposed EDCA scheme to apply the low rank matrix completion theory to the data gathering problem of WSNs [9]. Since EDCA only sample partial readings on each single sensor, the energy cost of sampling which is often ignored before can also be reduced.

In a recent work [13], the authors proposed an interesting in-network aggregation technique and exploited CS to reconstruct the data at the sink. Differently to our approach, the aggregation technique depends on the network topology and the design of the scarification matrix depends on the type of data, thus it cannot automatically adapt to complex spatial and temporal correlation characteristics.

In [10], the authors propose a 1-bit CS algorithm for data gathering in WSNs. In this method, instead of transmitting the fully quantized directly, 1-bit CS sends the sign of projection values. More recent work in this field include [11], which involve the capacity and delay analysis for data gathering with compressive sensing in WSNs, in which both single sink and multi sink network are considered.

III. COMPRESSIVE SENSING THEORY

This section describes the overview of CS and various reconstruction algorithms.

A. CS Overview

CS is a novel sensing paradigm that goes against the traditional understanding of data acquisition and can surpass the traditional limits of sampling theory [4] [12]. It has a surprising property that one can recover sparse signals from far fewer samples than is predicted by the Nyquist–Shannon sampling theorem. In the conventional paradigm, natural signals are first acquired at Nyquist- Shannon sampling rate, and then compressed for efficient storage or transmission [13].

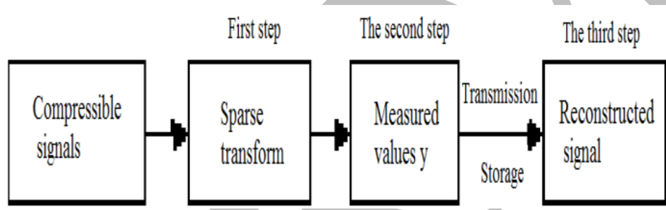

Fig. 2. Compressive Sensing Procedure

CS shift this paradigm by combining the sampling and compression into one step by measuring samples that contain the maximum information about the signal, this eliminates the need to acquire and store large number of samples only and drop the minimal values. The procedure of compressive sensing is shown in fig.2. CS relies on two principals [4] [14]:

Sparsity: This pertains to the signals of interest. CS exploits the fact that many natural signals (such as sound, image or seismic data) are sparse or compressible in the sense that they have concise representations when expressed in some suitable basis. When the basis is chosen properly, a large number of projection coefficients are zero or small enough to be ignored. If a signal has only k non-zero coefficients, it is said to be k-Sparse. If a large number of projection coefficients are small enough to be ignored, then signal is said to be compressible.

Incoherence: This pertains to the sensing modality. Coherence the coherence measures the largest correlation between any two elements of ϕ and Ψ. If ϕ and Ψ contain correlated elements, the coherence is large. Otherwise, it is small. CS is mainly concerned with low coherence. If Ψ is a $n \times n$ matrix with $\Psi_1,\ldots,\Psi_n$ as columns and φ is an $m \times n$ matrix with $\varphi_1, \ldots,\varphi_m$ as rows. Then coherence μ is defined as:

$\mu(\varphi,\Psi) = \sqrt{n}\ .\ \max|\varphi k, \Psi j|$ for $1 \leq j \leq n$ and $1 \leq k \leq m$

The basic idea of this theory: Let us assume that a discrete signal $X \in R^N$, which is presented by N×1 column vector, has sparse representation in some basis such as Fourier or Wavelet. Considering this sparsity concept, this signal can be expressed in term of the basis as:

$X = \sum_{k=1}^{N} ak\ \Psi k = \Psi a$

Where, Ψ is an N×N orthonormal basis matrix $\Psi = [\Psi_1, \Psi_2, \ldots, \Psi_N]$, Ψ_k, is a N×1 vector, and $a = [a_1, a_2, \ldots, a_N]$ is the N×1 column vector of the coefficient sequence of X in Ψ domain. Signal X is compressible or sparse in Ψ basis, if its coefficient vectors have a few large elements and many small or zero elements. In other words, most of the elements in 'a' are zero. Compressive sensing theory states that if signal X is K-sparse on Ψ basis, it can be captured and recovered from M non-adaptive, linear measurements ($k < M << N$) with a certain restriction. The sampled signal via CS is described as:

$Y = \phi X$

Where, $Y = [y_1, y_2, \ldots, y_M]$ is M×1 measurement matrix, $\phi = [\phi_1, \phi_2, \ldots, \phi_M]$ represents a M×N sensing matrix and each ϕ_i, i=1,2,3,...,N is a N×1 vector. It must be mentioned that ϕ is a random matrix, which can be assumed as second basis. Each element y_i in measurement matrix is a product of vector X and a vector ϕ_I from sensing matrix. We can substitute X with Ψ**a** then we can rewrite y as:

$Y = \phi X = \phi \Psi a = \theta a$

Where, $\theta = \phi \Psi$ is a M×N matrix.

Compressive sensing theory demonstrates that sparse signal can be recovered from M measurements if it can satisfy restricted isometric property (RIP). RIP states that ϕ and Ψ must be incoherent, which means that the rows of ϕ must not sparsely represent the columns of Ψ (and vice versa). Formally speaking, a θ matrix of size M × N satisfies the RIP of order K if it can be the minimum number such that:

$(1-\delta_k)\|a\|_2^2 \le \|\theta a\|_2^2 \le (1+\delta_k)\|a\|_2^2$

Where, $\delta_k \in (0,1)$ is a restricted isometric constant (RIC). Equation (4) must be hold for all a with $\|a\|_0 \le k$, and $\|a\|_0$ is l_0 norm which shows number of non-zero elements in a. l_p norm of vector a is defined as:

$\|a\|_p^p = \sum_{i=1}^{N} \|a\|^p$

RIP guarantees the exact recovery of x with high probability if

$M \ge \text{cont. } k \log \frac{N}{k}$

However, the recovery of the signal X from Y is an NP hard problem but it can be done through optimization. To do so, l_1 minimization is widely used for CS signal reconstruction, while l_0 minimization is computationally intractable. We can recover the coefficients of sparse signal a by solving l_1 norm minimization as follows

$\dot{X} = \Psi \acute{a}$; $\acute{a}\ \text{argmin}_{a \in R^N} \|a\|_{l1}$ s.t. $Y = \phi X$

B. Reconstruction algorithms

Many algorithms and their variants have been proposed in the literature. Most of these algorithms can be classified into following categories, to present the overview of reconstruction algorithms for sparse signal recovery.

1. Convex Relaxation:

This class of algorithms solves a convex optimization problem through linear programming [15] in order to obtain reconstruction. These methods are computationally complex but the number of measurements required for exact reconstruction is small. Basis Pursuit [16], Basis Pursuit De-Noising (BPDN) [16], modified BPDN [17], Least Absolute Shrinkage and Selection Operator (LASSO)*/ [18] are some examples of such algorithms.

2. Greedy Iterative Algorithm:

This class of algorithms solve the reconstruction problem by finding the answer, step by step, in an iterative fashion. The idea is to select columns of θ in a greedy fashion. In each iteration, the column of θ that correlates most with Y is selected. Conversely, least square error is minimized in every iteration and the stopping criterion for iteration varies from algorithm to algorithm. When the signal is not much sparse the recovery becomes costly. Algorithms, such as matching pursuit [19], orthogonal matching pursuit [20], threshold orthogonal matching pursuit, StOMP [21], etc., are examples of the greedy approach.

3. Combinatorial Algorithms

Through group testing this class of algorithms recovers sparse signal. They are extremely fast and efficient, as compared to convex relaxation or greedy algorithms but require specific pattern in the measurements; ϕ needs to be sparse and the algorithm presented in [22] is an example of the combinatorial approach.

4. Bregman Iterative Algorithms

For solving l_1 minimization problem, these algorithms provide a simple and efficient way. When applied to CS problems, the iterative approach using Bregman distance regularization achieves reconstruction in four to six iterations [23].

CS appears to be an excellent technique for data acquisition and reconstruction in WSNs which typically employs a smart fusion center (FC) with a high computational capability and several dumb front-end sensors having limited energy storage. In [31], authors propose a decentralized extension of a recent FBMP (Matching Pursuit method) method for reconstructing a signal ensemble with a joint sparsity structure at the nodes of a WSN requiring a minimal amount of transmitted information. The proposed work is robust to a reduction in the number of CS measurements or to node failures.

Penalized $\ell 1$ minimization algorithm is proposed in [32], where the sparse Fr´echet mean is used appropriately to make ℓ_1 minimization close to ℓ_0 minimization, since fewer measurements are needed for exact reconstruction with ℓ_0 minimization than with ℓ_1 minimization and a Fr´echet mean enhanced greedy algorithm, called precognition matching pursuit (PMP), where the sparse Fr´echet mean is used to estimate the support, i.e., the nonzero positions, of the sparse representation is also proposed

C. CS in WSNs

Wireless sensor networks are a special distributed sensor networks used to measure a certain spatially-varying phenomenon, such as variation of temperature over a certain geographical area. The main task of sensor networks transmits the interest information collected by sensor nodes to the sink as in Figure 1. This can be implemented using theory of compressed sensing and delivering projection observation to the sink.

Considering the inherent inefficiencies of transform coding and the availability of sparsity or compressibility in WSNs signals due to spatio-temporal correlations within the sensor readings, [12] CS is gaining researcher's attention as a potential compression approaches for WSNs. In CS, most computation takes place at the decoder (sink), rather than at the encoder (sensor nodes); thus, sensor nodes with minimal computational performance can efficiently encode data. There are few more advantages of using CS in WSNs: First of all, CS is a compressive method, which can be used to data aggregation in WSN. Also it helps in graceful degradation in the event of abnormal sensor readings and low sensitivity to packet loss. As known to all, the energy problem is one of the most important issue in WSN. So, CS can help to reduce the traffic, which also be a part of energy saving. CS is a promising approach for removing redundancy during sensing operations in WSNs. CS for WSNs exploits only temporal (intra-signal) structures within multiple sensor readings at a single sensor and does not exploit spatial (inter-signal) correlations amongst nearby sensors. Due to number of advantages many researchers are doing research on compressive sensing in WSNs.

Many researchers have used the CS for data gathering in WSNs for improving the efficiency of the network such as in[2,5,6,7,8,9,10,11,12].

IV. APPLICATIONS OF CS

Compressive sensing is an attractive tool to acquire signals and network features in networking system. In this section, we present a few interesting compressive sensing applications in networking domain.

1. Wireless Sensor Networks

CS has its applications in data gathering for large wireless sensor networks (WSNs), consisting of thousands of sensors nodes are densely deployed [5]. This approach of using compressive data gathering (CDG) helps in overcoming the challenges of high communication costs and uneven energy consumption by sending 'm' weighted sums of all sensor readings to a sink which recovers data from these measurements. Although, this increases the number of signals sent by the initial 'm' sensors, but the overall reduction in transmissions and energy consumption is significant since m Â« n (where n is the total number of sensors in large-scale WSN). This also results in load balancing which in turn enhances life-time of the network. In [24], the authors propose a joint optimization method for reducing the cost of data gathering. They propose a centralized iterative algorithm for joint optimization of the energy overlap and distance between sensors in each cluster and simulation results show that significant savings in transport cost with small reconstruction error is achieved.

2. Channel coding.

As explained in [25], CS principles (sparsity, randomness, and convex optimization) can be turned around and applied to design fast error correcting codes over the reals to protect from errors during transmission.

3. Erasure Coding

Compressive sensing can be utilized for inexpensive compression at encoder. CS is again utilized as a channel coding scheme in order to enable correct recovery of the compressed data after passing through erasure channels. Such compressive sensing erasure coding (CSEC) techniques [26] are not a replacement of channel coding schemes; rather they are used at the application layer, for added robustness to channel impairments and in low-power systems due to their computational simplicity. CSEC is achieved by nominal oversampling in an incoherent measurement basis.

4. Distributed Compression in WSNs

Distributed Source Coding is a compression technique in WSNs in which one signal is transmitted fully and rest of the signals are compressed based on their spatial correlation with main signal. When sudden changes occur in sensor readings DSC performs poorly, as these changes reflect in correlation parameters and main signal fails to provide requisite base information for correct recovery of side signals. Only spatial correlation is exploited in DSC, while under no-event conditions, sensor readings usually have a high temporal correlation as well. In [27], authors present a distributed compression framework which exploits spatial as well as temporal correlation within WSN. Compressive sensing is used for spatial compression among sensor nodes and temporal compression is obtained by adjusting number of measurements as per the temporal correlation among sensors. When sensor readings are changing slowly, few measurements are generated. Proposed framework features low complexity single stage encoding and decoding schemes as compared to two stages encoding and decoding in previous state-of-the-art, while keeping the compression rate same.

One of the most well-known CS technique proposed for correlated signals is the distributed compressive sensing technique (DCS) [30]. DCS introduces a greedy algorithm-based joint signal recovery method, which reconstructs different signals acquired by sensor nodes in a WSN where these signals are assumed to satisfy pre-defined joint sparsity models.

5. Network Security

CS can be used as an effective tool for provision of network security. As one example application of CS in network security include, clone detection, aiming to detect the illegal copies with all of the credentials of legitimate sensor nodes, is of great importance for sensor networks because of the substantial impact of clones on network operations like routing, data collection, and key distribution, etc. Authors in [28] propose a novel clone detection method based on compressive sensing claiming to have the lowest communication cost among all detection methods. They exploit a key insight in designing their technique that the number of clones in a network is usually very limited. In [29], authors consider the compressed sensing based encryption and proposed the conditions in which the perfect secrecy is obtained.

V. CONCLUSION

Compressive sensing theory is applied to WSNs so that the energy loss can be reduced in signal acquisition, transmission and the lifetime of the network is enhanced. CS theory asserts that one can recover certain signals from far fewer samples or measurement than traditional method use. This paper reflects the review of novel compressive sensing paradigm and CS in WSNs. Also, various reconstruction algorithms are described and finally the various applications of CS in network domain are presented.

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