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A COMPREHENSIVE REVIEW ON THE IMPACT OF COMPRESSED SENSING IN WIRELESS SENSOR NETWORKS

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Abstract- Sensor networking is a promising technology that facilitates the monitoring of the physical world using tiny, inexpensive wireless devices that are spatially distributed across a wide region. These networks are highly constrained in power, computational capacities and memory. Incorporation of techniques based on the concept of Compressed Sensing (CS) which aims to encode sparse signals using a much lower sampling rate than the traditional Nyquist approach has revolutionized the wireless network scenarios. An exhaustive survey on the impact and applications of CS in WSN and research challenges has been presented in this paper.

Index terms*:* Compressed Sensing, Data Aggregation, Data Recovery, Distributed Compressed Sensing, Kronecker Compressed Sensing, Wireless Sensor Networks.

I. INTRODUCTION

Wireless Sensor Networks (WSN) are the convergence of micro electro-mechanical systems technology, wireless communications and digital electronics. They find applications in military, environment, home, health and other commercial areas [1, 2]. Sensor nodes are constrained in power, computational capacities and memory. Compressed sensing (CS) holds significant improvements to these constraints. According to CS theory, small number of random linear measurements can be used to exactly reconstruct sparse signals and information [3]. CS can acquire a sparse signal from a small set of incoherent measurements with a sampling rate lower than Nyquist rate. CS plays a significant role in the next generation wireless networks, since experimental evidences prove that signals in wireless applications are sparse [4]. Incorporation of CS theory in WSNs leads to lower power consumption, lower time delay, higher probability of data transmission, reduced traffic, energy management and cost [5]. Some applications of compressive sensing over networks have been demonstrated by Feizi et al [6] and Xiaoyan in [7]. It has been concluded that the significant difference between CS and traditional information theoretic approaches is at their decoding side. The CS decoder uses linear or convex optimization whereas the optimal traditional decoders are highly complex [6]. Contrary to the Shannon's sampling theorem, CS is based on the fact that a signal that is sparse in certain representations can be recovered, by sampling it at the rate far below the Nyquist rate. CS has several advantages over the traditional sensing making it very attractive for WSN applications in particular. CS compresses a signal before it is recorded, where as traditional sensing compresses a signal after sensing. The application of CS based schemes in visual sensor networks has been presented in [8].

This paper is organized as follows: Section II gives a brief overview of CS. An extensive survey on the impact and applications of CS in WSN is presented in Section III. Future directions and research challenges are suggested in Section IV. The concluding remarks of the paper are given in Section V.

II. COMPRESSED SENSING – AN OVERVIEW

A brief overview on compressed sensing is presented here. Given a signal $x \in \Re^n$ and a measurement system that acquires m linear measurements, a standard finite-dimensional CS model is mathematically represented as $y = Ax$, where A is an $m \times n$ sensing matrix and

$y \in \Re^m, m << n$ [9]. The entire process of CS consists of signal sparse representation, linear encoding and measurement collection and sparse recovery [4].

If x is a k-sparse vector, i.e., the number of non-zero entries of x is no more than k, it is denoted by $\|x\|_0 \leq k$. Since y is recorded by a sensor, while x remains unknown, CS theory finds out the condition under which x can be recovered from y. When y is contaminated with noise, it helps how to guarantee the recovery is close to x. The system $y = Ax$ is an underdetermined system, with infinite number of solutions. The sparsest solution is found out by solving

$$\min_x \|x\|_0 \ \textit{subject to } Ax = y \qquad (1)$$

Since, this combinatorial problem is NP-hard, the ℓ_0 norm is replaced by ℓ_1 norm, and the problem is redefined as

$$\min_x \|x\|_1 \quad \textit{subject to } Ax = y \qquad (2)$$

which is convex and can be transformed into a linear program. Real world sensing applications involve noise due to imperfect sparsity and sensors [4]. To incorporate them, the sensing model is defined as $y=Ax + w$, where w is an n-dimensional vector of noise or measurement error. The vector y comprises of the noisy linear measurements of x. The ℓ_1 minimization problem that penalizes the violation of $y=Ax$ is written as

$$\min_x \|x\|_1 \quad \textit{subject to } \|Ax - y\|_2 \leq \varepsilon \qquad (3)$$

$$\min_x \|x\|_1 + \frac{\mu}{2}\|Ax - y\|_2^2 \qquad (4)$$

Equations (3) and (4) will have the same solution if the parameters ε and μ are properly chosen.

Sparse representation is the fundamental of CS and it is about expressing the information of a signal by a minimum number of real or complex numbers (Figure 1). It involves the choice of dictionary or sparsifying transform like gradient operator, curvelet transforms etc. In CS, the signal is recovered from A and y.

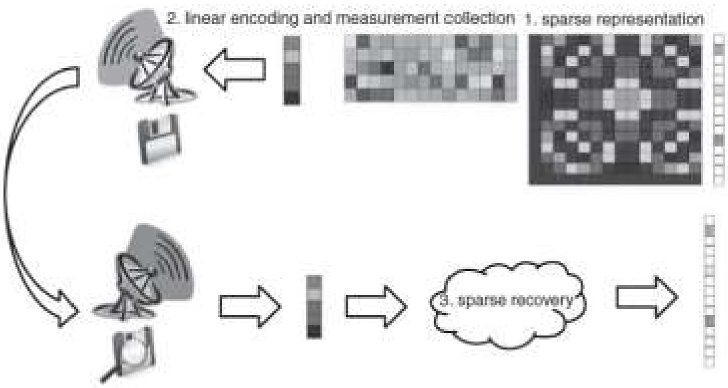

Figure. 1 Compressed Sensing [4]

The number of measurements required for recovery is determined by the quality of measurements. Alsheikh et al. have addressed the problem of transformation of source data collected by sensor nodes into sparse representation with few nonzero elements [10]. They have proposed an effective method that extracts population sparsity of the data, a sparsity ratio guarantee scheme and a customized learning algorithm of the sparsifying dictionary.

Incorporation of CS in communication networks, for detection and estimation of wireless signals, source coding, multi-access channels, data acquisition in sensor networks, network monitoring etc. has shown significant performance gains [11]. Sensor data with some structural regularity could be estimated in an energy efficient way at a distant fusion center through Compressive Wireless Sensing [12]. Haupt et al have described how CS techniques could be used to reconstruct networked data from WSNs and general multihop networks [13]. They have highlighted the fact that universal sampling and decentralized encoding are two significant features of CS which promises a new paradigm for networked data analysis. Luo et al have proposed two different ways of CS – plain CS and hybrid CS in the form of data aggregation mechanism to be incorporated in the networking layer of WSNs [14]. It has been illustrated that incorporation of hybrid CS results in significant improvement in the throughput and application of plain CS may not bring any improvement. Shen et al. proposed non-uniform CS for heterogeneous WSNs for improved performance capitalizing on both compressibility and heterogeneity [15]. The proposed method provided a more accurate temporal-spatial profile for a minimum energy. Liu et al. have proposed a new adaptive CS for WSN [16]. In this algorithm, a sparse additional projection vector is built using a new metric named total coefficients power to guide the node selection and the coefficients are determined by adopting differential entropy. The proposed algorithm is more energy efficient, obtained good reconstruction performance with reduced communication cost when compared to classical CS.

a. Distributed CS

Baron et al. introduced a new theory for Distributed CS (DCS) which enabled new distributed coding algorithms for multi-signal ensembles which capitalize on intra- and inter- signal correlation structures [17, 18]. The term 'joint sparsity' of a signal ensemble was the underlying concept of the DCS theory. The fundamental performance limits of DCS recovery for jointly sparse signals in a noiseless measurement setting were obtained. Algorithms for joint recovery of multiple signals from incoherent projections were also proposed. DCS was found to be applicable in sensor arrays and network problems.

The two frameworks dealing with sparsity and compressibility of multidimensional signals and signal ensembles, DCS and Kronecker CS (KCS) have been compared by Caione et al. in [19]. They have concluded that in real deployment, reduced power consumption and prolonged lifetime is guaranteed by DCS. Youness and Hassan investigated on energy preservation in large-scale WSNs utilizing DCS [20]. They concluded that power consumption could be reduced by reducing the data rate traffic of the network which is in turn done by using either data correlation and sparsity in one dimension or the spatial sparsity among clustered sensor nodes. It was observed that DCS improved the network lifetime too. Hu and Yang have proposed a Spatial Correlation-based DCS (SCDCS) model and algorithm for WSNs [21]. Energy efficient compression and reconstruction of sensor observations are done based on coding and decoding algorithm of SCDCS, in which spatial correlation and joint sparse models between the sensor nodes have been used. The same authors have proposed a Wavelet Transform-based DCS (WTDCS) algorithm for compression and reconstruction of sensor observations with spatial correlations [22]. It was proved that WTDCS outperformed the conventional distributed wavelet transform algorithm in energy efficiency and reconstruction accuracy.

b. Kronecker CS

The focus of conventional CS has been on 1-D signals and 2-D image problems. Hence the construction of sparsifying bases and measurement systems for multidimensional signals becomes complicated due to their higher dimensionality. To solve this issue, Duarte and Baraniuk have proposed the use of Kronecker product matrices in CS [23]. These matrices act as sparsifying bases that jointly model the structure present in all of the signal dimensions and they can also represent the measurement protocols used in distributed settings. The authors have derived the analytical bounds for sparse approximation of multidimensional signals and the CS recovery performance.

c. Sequential CS

CS allows perfect recovery of sparse signals but it requires prior knowledge of the sparsity of the unknown signal. To overcome this problem, Malioutov et al. proposed sequential CS, in which the observations are available in sequence [24]. Hence for any recovery method, a sequence of candidate reconstructions is available. The authors have proposed a method to estimate the reconstruction error for every candidate. This estimate does not depend on any recovery method nor does it require a prior knowledge of the sparsity of the unknown signal.

III. IMPACT OF COMPRESSED SENSING IN WSN

An exhaustive survey on the impact of CS in WSN has been presented in this section. It includes data aggregation, data recovery, routing, transmission, network security, storage, event detection, source localization and target detection. Figure 2 depicts the impact of CS in WSN corresponding to the Open System Interconnection (OSI) model.

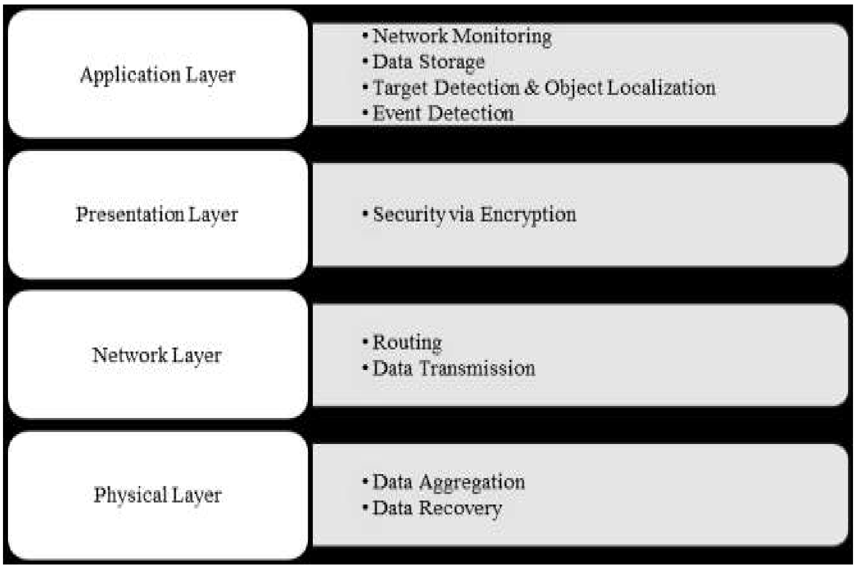

Figure 2. Impact of CS in WSN corresponding to OSI Model

a. Data Aggregation

Data aggregation is a very crucial operation in WSNs because of the constraint of limited energy supply. A new paradigm for efficient data aggregation in WSNs is facilitated by CS. Figure 3 depicts the CS based data aggregation in WSN. CS based signal and information aggregation in WSN and Internet of Things has been proposed by Li et al. [25]. Accurate data reconstruction and lower energy efficiency is obtained using a cluster-sparse reconstruction algorithm. Liu et al. have proposed a novel compressive data collection for WSNs adopting a power-law decaying data model [26]. A random projection-based estimation algorithm has also been proposed for this data model. The methodology required fewer measurements, thus greatly reducing the consumption of energy. The capacity and delay analysis for data gathering with CS in single-sink and multi-sink WSNs have been presented by Zheng et al in [27].

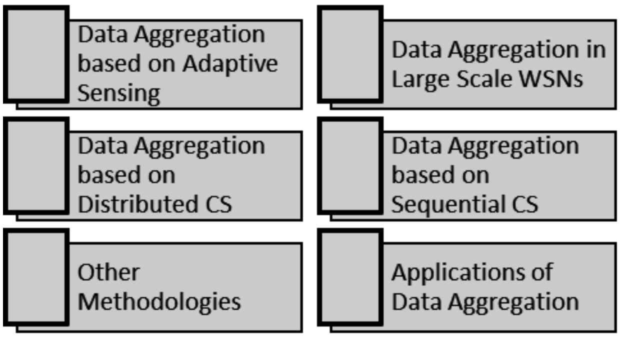

Figure. 3 CS based Data Aggregation in WSN

1. Data Aggregation based on Adaptive Sensing

Chen et al proposed a Distributed Adaptive Sparse Sensing (DASS), considering the sensing energy cost in order to improve the overall energy efficiency [28]. Instead of using fixed or random sampling patterns, they proposed an adaptive learning of signal model based on the measurements. The method outperformed traditional sensing methods and had minimal on-board computation, no inter-node communications and better reconstruction performance.

An Adaptive Compressive Sensing (ACS) based sample scheduling mechanism for WSNs has been developed by Hao et al. in [29]. ACS ensures high sensing quality at low sample rate by adaptively estimating the minimum required sample rate subject to given sensing quality on a per-sampling-window basis and adjusting the sensors' sample rates accordingly. Low power WSN with CS theory has been proposed by Balouchestani in [30]. Power management schemes are utilized to decrease power consumption and increase the lifetime of sensors in WSNs. A CS-based adaptive data gathering methodology for WSNs was presented by Wang et al in [31].

2. Data Aggregation based on Distributed CS

Masoum et al. proposed a distributed compressive sensing technique for data gathering in WSNs [32]. A probabilistic model of the signals is built using Bayesian inference and the common sparse signal is recovered using belief propagation algorithm is used as decoding method. CS based distributed correlated data gathering in WSN was proposed by Leinonen et al in [33]. A distributed method based on joint correlation pattern of a multi-dimensional WSN signal ensemble through Kronecker sparsity basis is proposed. It resulted in significant reduction of data traffic in correlated data gathering in multi-hop WSNs. An algorithm based on compressive distributed sensing using random walk has been proposed for data acquisition in WSNs by Sartipi and Fletcher [34]. The CS problem has been modeled with code design for a set of parallel channels, which has been used to formulate a rateless code degree distribution.

Laifenfeld and Bilik proposed a CS-based distributed joint communication-acquisition scheme for WSNs over fast fading wireless communication channels [35]. The WSN is considered to time-slotted where the probability of each sensor to transmit in every slot is p. It has been shown that the total latency and energy transmission in the WSN is affected by p. A distributed compressive data gathering methodology in low duty cycled WSNs has been proposed by Wang et al in [36]. In this approach all the nodes operate in a decentralized mode and all data can be gathered from any arbitrary node within the sensor network. An energy-efficient sensing in WSN using CS has been proposed by Razzaque and Dobson in [37]. The effectiveness of CS and distributed CS has been investigated using several experiments proving the significant reduction in sensing energy and thereby the overall energy costs in WSN.

3. Data Aggregation based on Sequential CS

Hao et al. proposed sequential CS in WSNs, a new signal acquisition framework [38]. New methods for adaptively adjusting the number of CS samples in WSNs have been proposed. Homotopy algorithm has been applied to update the reconstructed signals. The proposed method reduced the computational complexity and saved processing time. Sequential CS with progressive signal reconstruction in WSNs was proposed by Leinonen et al. in [39]. A sequential framework for compressed acquisition and progressive reconstruction has been developed based on sliding window processing. The current sensors' readings could be efficiently reconstructed by the sink by capitalizing on the joint compressibility via Kronecker sparsifying bases. A dynamic trade-off between the CS recovery performance and decoding complexity could be obtained by adjusting the window size.

4. Data Aggregation in Large Scale WSNs

The two major technical challenges in large scale WSNs are reduction of global communication cost and energy consumption load balancing. Luo et al. have presented the application of compressive sampling theory to sensor data gathering to effectively address the aforementioned technical challenges in large scale WSNs [40]. The problem of data acquisition in large distributed WSNs has been addressed by combining hierarchical routing method and compressive sensing by Zou et al. in [41]. CS theory has been applied to gather and reconstruct the sparse signals in energy constrained large scale WSN by Yang et al. in [42]. Sparse presentation of signal, observation matrix and design of reconstruction algorithm has also been discussed.

5. Other Data Aggregation Methodologies

Energy efficient data collection in WSN has been accomplished by integrating CS and clustering in WSN [43]. The optimal number of clusters for minimum power consumption has also been analyzed. A new compressive data gathering method called Minimum Spanning Tree Projection (MSTP), has been proposed for energy efficient WSNs [44]. The simulation results proved that the proposed method outperformed the existing data aggregation methods by decreasing the communication cost, distributing the energy consumption loads and thus improving the network lifetime.

Energy-efficient and high-fidelity data collection through compressed data aggregation has been developed by Liu et al in [45]. Here diffusion wavelets have been used to obtain a sparse basis characterizing the spatial and temporal correlations. A mixed integer programming formulation along with a greedy heuristic has been proposed to solve the minimum-energy compressed data aggregation problem. Several algorithms to exploit the temporal correlation of sparse signals in WSNs have been proposed by Alwakeel et al. in [46]. The performance of these approaches was evaluated using synthetic and real data sets at different noise levels.

A Graph Based Transform (GBT) to sparsify the sensor data from irregularly positioned sensors was proposed by Lee and Ortega in [47]. A heuristic design of data gathering has been discussed and the proposed approach has outperformed the conventional CS approaches in total power consumption. Li et al. have presented a methodology for data gathering in Network Compressed Coding (NCC) enabled WSNs in [48]. Network coding has been used to adapt to the dynamic nature of WSNs. The data gathering efficiency of NCC outperformed the conventional NC schemes by 20%. A power-efficient hierarchical data aggregation using compressive sensing in WSNs has been developed by Xu et al. in [49]. In this approach, multiple compression thresholds are set up adaptively depending on cluster sizes at different levels. A multi-resolution hierarchical structure has been integrated with CS to optimize the amount of data transmitted.

6. Applications of Compressed Data Aggregation

An acoustic signal acquisition system based on wireless sensor networks and CS theory to collect the crawling noise of granary castaneum adults was proposed by Han et al. [50]. This could be used to reduce the huge losses incurred by stored grain pests. The impact of CS technique in a cardiac monitoring WSN has been presented by Pinheiro et al. [51]. Three different cardiac signals Ballistocardiogram (BCG), Electrocardiogram (ECG) and Photoplethysmogram (PPG) were compressed and recovered. The implications of data reliability and energy management have also been presented. A compressive sensing framework for energy efficient signal acquisition in WSN for monitoring 1-D environmental information has been presented by Chen and Wassell [52]. The authors have demonstrated a remarkable reduction in the number of samples required to obtain minimum reconstruction error. A map-based CS model for WSN architecture for sensing natural events has been proposed by Mahmudimanesh [53]. Selection of suitable geometric framework and the use of spatial attributes of operational environment aids in better representation of the compressible vector view of environmental signal.

b. Data Recovery

The most significant advantage of CS is that it helps to recover a high-dimensional signal from a small set of measurements. The different techniques used for data recovery in WSNs are presented below. Figure 4 depicts the various CS based data recovery methods in WSN.

Figure 4. CS based data recovery in WSN

1. Data recovery using matrix completion techniques

An Efficient Data Collection Approach (EDCA) for data query in WSNs was proposed by Cheng et al. in [54]. The spatial and temporal correlations in WSNs are used to minimize energy consumption. The original data is recovered efficiently by matrix completion techniques. Fragkiadakis et al. proposed a joint compressed-sensing and matrix-completion for efficient data collection in WSNs [55]. Missing information due to packet loss is recovered using matrix-completion techniques efficiently.

2. Data recovery using Bayesian methods

Accurate recovery of CS data in WSNs under the framework of Bayesian estimation has been proposed by Masiero et al. in [56]. The data collected by an indoor WSN test bed has been analyzed and the effectiveness of the proposed reconstruction algorithm has been validated. A joint sparse signal ensemble reconstruction in a WSN using decentralized Bayesian matching pursuit was proposed by Tzagkarakis et al. [57]. In this methodology, reduced amount of data transmissions among the sensors and a central node preserved the sensors' limited resources.

3. Other Data Recovery methods

Leinonen et al. proposed a novel method for compressed acquisition and progressive reconstruction of multi-dimensional correlated data in WSNs [58]. It was based on sliding window processing, where the sink collects CS measurements of sensor samples periodically. The current WSN samples are reconstructed instantaneously by using the spatio-temporal correlation via Kronecker sparsifying bases. Li and Qi proposed a Distributed Compressive Sparse Sampling (DCSS) algorithm based on sparse binary CS measurement matrix for approximate sparse recovery problem in multi-hop WSNs [59]. It was concluded that the in-network communication cost and computational burden was greatly reduced due to the sparsity and binary properties of the measurement matrix. Wang et al. observed that local adaptive sparsity could be achieved and local correlation in sensed data could be exploited by introducing an autoregressive (AR) model into the reconstruction of sensed data [31]. Evaluation of the recovered data at the sink was done utilizing the relation between error and measurements of successive reconstructions. Brunelli and Caione have presented a methodology for sparse recovery optimization in WSNs with sub-Nyquist sampling rate [60]. An optimal under-sampling ratio has been defined and a reconstruction algorithm that performs best with reduced energy consumption has also been proposed. A novel framework combining CS and principal component analysis, namely SCoRe1: Sensing, Compression and Recovery through online Estimation for WSNs has been proposed by Quer et al in [61]. A sparsity model that uses CS for online recovery of large datasets in real WSN scenarios has been proposed. The performance limits of CS when used as a recovery tool in WSN has also been analysed.

c. Network Routing

WSNs are extremely versatile and can be deployed in varying density for different applications. Irrespective of the varied objectives of sensor applications, it is necessary that the basic task of sensing, collecting, processing and transmitting of data is done efficiently. This requires the development of energy-efficient routing protocols to set up paths between the sensor nodes and the data sink [62]. Incorporation of CS in WSN routing has yielded significant improvements.

A novel approach to WSN dynamic routing topology inference from indirect measurements collected at the data sink has been proposed by Liang and Liu in [63]. The same authors have addressed the problem of general WSN routing topology tomography as a novel CS problem and presented a decoding algorithm [64]. A Fast Routing Topology Recovery (FRTR) algorithm has been proposed and its performance analysed. Chengtie et al. have proposed a cross-layer congestion control algorithm based on CS in WSN where there is simultaneous occurrence of node-congestion and link-congestion [65]. The controller design involves two major steps. First, when the signal enters into a bottleneck node, the original signal is projected compressively by measurement matrix, to reduce its length. Secondly the signal reconstruction is implemented by minimum $\ell 1$-norm method. A CS-based inter-cluster multi-hop routing, referred to as ICCS was proposed for WSNs by Nguyen et al. [66]. CS measurements are relayed from each cluster head to the base station. A routing tree is formed between the cluster heads and the base station by a greedy algorithm.

A CS-based approach for Path Reconstruction (CSPR) in WSNs has been proposed by Liu et al. [67, 68]. The sparse path representation is encoded into packets and the path vector and the represented routing path are recovered from a small amount of packets using CS technique. The performance of CSPR is evaluated both in real-time experiments and simulations and it was found to outperform the existing approaches in various network settings. Wang et al. have proposed a CS-based random routing for multi-hop WSNs [69]. The proposed scheme outperformed the existing approaches in signal reconstruction and greatly minimized the routing energy consumption.

A distributed algorithm which uses local minimization for the dynamic construction of a routing path for CS based aggregation was proposed by Tsai et al. [70]. It was observed that this algorithm did not require the complete knowledge of the global network topology, reduced data traffic and lower overhead.

A random routing algorithm for heterogenous WSN structured based on cobweb model was proposed by Hao et al [71]. Since a conventional CS-based data aggregation scheme is unsuitable for heterogenous WSNs, a novel data gathering scheme based on CS along with the random routing algorithm was proposed. Mehrjoo et al. proposed a CS-based novel intelligent energy-efficient delay-aware routing in WSN [72]. In this algorithm CS is employed along with Particle Swarm Optimization to reduce the communication rate and to build up the data aggregation trees respectively. The proposed algorithm outperformed LEACH and shortest-path routing in improving the network lifetime. CS-based random walk routing for WSN was proposed by Nguyen [73]. It was observed that the combination of random walk routing and CS effectively saves energy and increases network lifetime.

Nguyen and Teague have proposed a CS-based energy efficient random routing in WSNs by using random walk to collect data [74]. The trade-off between exploring the measurement matrix and determining the length for random walks to achieve minimum energy consumption has been investigated.

d. Network Transmission

Transmission of large amount of data in WSNs hinders the applicability and the reliability of large scale WSNs deployment. CS-based in-network processing results in compressed sensory data and its accurate recovery in the sink. The transmission cost is decided by two factors namely, each CS measurement transmission cost which is in turn depends on the measurement matrix and the number of CS measurements [75]. A survey on the various data compression schemes that could be used to minimize the data transmitted over wireless channels have been presented by Srisooksai et al in [76].

A sparsest random scheduling for compressive data gathering in WSN has been proposed by Wu et al in [75]. The proposed method decreases each measurement transmission cost from O(N) to O(log (N)), without increasing the number of CS measurements. A design method for generation of representation basis, according to the sparsest measurement matrix and sensory data, has also been proposed to satisfy the restricted isometric property. Hwang et al. proposed an SNR efficient transmission for CS based WSNs [77]. A novel sensor selection scheme and design of signaling channel has been proposed with the assumption that the measured signals at each sensor are correlated and sparse at some basis domain. Xie and Jia have proposed a transmission efficient clustering method for WSNs using CS [78]. The optimal size of clusters that can lead to minimum number of transmissions has been determined using an analytical method that analyses the relationship between the size of clusters and number of transmissions in the hybrid CS method. A centralized clustering algorithm based on results of the analytical model has also been implemented. Bajwa et al. have proposed a joint source-channel communication for distributed estimation in sensor networks [79]. It was observed that phase-coherent transmissions from the sensors enable exploitation of the distributed beamforming gain resulting in significant reduction in power consumption. Chen et al. have discussed the benefit of using tight frames for robust data transmission and compressive data gathering in WSNs [80]. It was proved that tight frames outperformed the common CS Gaussian matrices in the average mean squared error, making the data transmission robust and reducing the communication cost. Efficient computation of robust average of CS data in WSNs in the presence of sensor faults has been discussed by Chou et al. in [81]. This method exploits the advantages of CS for efficient data transmission.

e. Network Security

Security in WSN is a challenging and significant problem due to the scale and resource limitations. The security requirements, vulnerabilities and mechanisms in WSN has been carefully presented by Sen in [82]. The energy constrained nature of WSNs makes the use of cryptographic techniques such as encryption and hashing very difficult. Hence CS-based encryption has an inherent advantage for security.

Zhao and Huang have discussed on CS applied to WSN security [83]. They have proposed a security scheme for WSNs, in which two legitimate nodes establish a common secret key using the joint channel characteristics of the wireless channel. The measurement matrix and reconstruction matrix for the two nodes are constructed based on the established keys. The proposed scheme ensures improved security with low computational complexity.

Qi et al. have proposed a hybrid security and CS-based sensor data gathering scheme [84]. The hybrid security includes 8-bit integer chaotic block encryption and a chaos-based message authentication codes. Since the proposed method is a lightweight security scheme, the complexity and energy consumption is reduced. A CS-based clone Identification (CSI) methodology in WSNs has been proposed by Yu et al. [85]. Clone detection, which is the detection of illegal copies that have all credentials of a legitimate sensor node, is of significance in WSNs. The proposed method exploits the sparse nature of this issue and

hence achieves a very low communication overhead. The application of CS in network monitoring has been presented by Haupt et al [86]. An implementation of energy efficient data compression and security mechanism in clustered WSN has been presented by Nagdive and Ingole [87]. The SET-IBS protocol is used for encrypting the data on the sensor node.
A secure compressed reading is of critical significance in smart grids [88]. It was observed that real-world meter data exhibited strong temporal correlations and indicated sparsity in certain domains. A dependable CS-based scheme for data transmission has been proposed to make the meter reading secure and reliable.

f. Data Storage

A promising and effective storage and search mechanism for collecting, storing and querying data in the energy constrained WSN is a key challenge [89]. Cstorage, a CS- based fully distributed and efficient data storage scheme for WSNs has been proposed by Talari and Rahnavard in [90]. The compressibility of natural signals and the broadcast property of wireless channels are exploited because of which Cstorage, requires much smaller number of transmissions compared to existing algorithms. Each node obtains one compressed measurement after a probabilistic readings dissemination phase. The sample is later queried by the data collector for recovery of sample. Yang et al. proposed Compressed Network Coding for Distributed Storage (CNCDS) in WSNs [91, 92]. The proposed algorithm utilizes CS theory and network coding technology and exploits the correlation of sensor readings. The scheme reduced the number of transmissions up to 55%, number of receptions up to 74% and the CS recovery mean squared error by 76% when compared with the conventional ICStorage scheme. Gong et al. proposed Spatio-Temporal Compressive Network Coding (ST-CNC) for energy-efficient Distributed Data Storage (DDS) in WSN [93]. The CS based DDS scheme exploit the spatial correlation among sensor readings from geographically neighbouring nodes.

g. Event Detection

Event detection is one of the significant applications of WSNs. But noisy sensed data of sensors and wireless channel noise never guarantees accurate detection. CS based technologies for detection of sparse events has been successfully proposed to overcome these issues. The problem of sparse event detection in WSN is formulated as a CS problem by Meng et al. [94]. The sparse event is assumed to have a binary nature, and Bayesian detection is employed using this prior information. The proposed detection algorithm outperformed the $\ell 1$-magic algorithm.

Jellali et al. introduced CS-based schemes for new deterministic sensors for sparse events detection in WSN based on observation or the channel matrix correlation and energies measures [95]. In order to prove that separation of detecting and counting steps allows reduction in computational burden and improves performance, they have proposed a two stage version of Greedy Matching Pursuit (2S-GMP).

CS-based scheme for sparse events detection and reconstruction in a large WSN has been proposed by Yan et al. in [96]. Game theory has been used to partition the nodes into *C* sets in a purely distributed way with an aim to save energy and extend the network lifetime. In each specified time slots, a part of the *C* sets nodes are woken up and the rest of the nodes are in sleep mode. CS theory is applied to gather and reconstruct the sparse signals based on the proposed sleeping strategy and exploiting the spatial sparsity of the event in the local area.

Liu et al. have proposed a CS-based multiple event detection scheme [97]. The reconstruction of source signal containing multiple simultaneous events has been done using the efficient recovery algorithms of CS. The detection accuracy has been improved capitalizing on the temporal correlation of data.

The sparse event detection in WSN has been modeled as a compressive support recovery problem [98]. The reconstruction algorithm uses sequential compressive sensing, capitalizing on the sparse and binary nature of the event signal. The proposed method outperforms the existing schemes and exhibits robustness at low Signal to Noise Ratios (SNRs). Shirvanimoghaddam et al. have proposed the sparse event detection in WSN using analog fountain codes [99]. They have shown that the sensing process in WSNs produces an equivalent analog fountain code in the sink node, whose code parameters are determined based on the sensing capability of sensor nodes and channel gains. The probability of false detection of the proposed method was analyzed and found to be negligible.

h. Object Localization & Target Detection

The recent spur of interest in location-based services has increased the demand on accurate and robust object localization techniques. Multi-resolution search and expectation maximization algorithms for source localization consume high energy and have poor localization accuracy. Hence they are unsuitable for energy-constrained WSNs. Wang et al. proposed a Bayesian CS approach for robust object localization in WSNs [100]. This method works by building location fingerprinting based on both line-of-sight (LOS) and non-line-of-sight (NLOS) measurements and is applicable to mixed LOS/NLOS environment. Huang et al. proposed a Multi-source Localization algorithm via Sparse Reconstruction based on Fully Distributed structure (MLSR-FD) in WSNs [101]. Each sensor node transmits and receives energy observations from nodes within one-hop communication range. To locate sources using sparse reconstruction, a multi-resolution redundant dictionary is used. The estimates of the local source position of the nearest nodes are fused and converged to the global estimates by the proposed algorithm. The target localization in WSN is investigated as CS problem by Bo and Linhua in [102]. The target spatial domain is discretized by grids and the target localization is a sparsity seeking problem, solved by an Improved Orthogonal Matching Pursuit (IOMP) algorithm. Gao et al. introduced a CS-based model to formulate the problem of target detection in WSN [103]. A CS-based probabilistic sensor management for target tracking in WSNs was proposed by Zheng et al. [104, 105]. The sensor management problem is modeled as the problem of ascertaining the probability of transmission at each node, in order to optimize a given performance metric. At any given time instant, considering the energy-constraint, the trace of the Fisher Information Matrix (FIM) is maximized, in order to determine the optimal values of the probabilities of transmission.

IV RESEARCH CHALLENGES

Network lifetime, computational ability and bandwidth constraints are the three major challenges in WSNs. Research works in CS techniques that aim to address these three challenges for application in WSN are required.

- Development of suitable techniques to reduce the number of samples required for recovery of the sampled signal will be a great energy saver.
- Sample scheduling is a crucial issue in WSNs. An efficient sampling schedule that achieves a high sensing quality at a low sampling rate is a need of the hour.
- Dynamic routing topology for large scale WSNs under varied scenarios with incomplete path measurements due to loss in real world communication environments is an active research area.
- Energy efficient algorithms for robust data transmission in WSNs will help in saving the battery life time.
- Efficient and scalable techniques for securing and monitoring large-scale networks like Smart Grids etc. will be a great asset.

- CS based data storage schemes that will address the challenges of similarity, spatio-temporal similarity search and the non-uniformity of sensor networks are needed.
- Research with a greater focus on the sparse behaviors of WSNs using CS is required.
- CS based optimized placement of sensors and number of measurements required in WSNs will accelerate CS based revolution in WSN.
- Algorithms for CS based object localization and target detection suitable for different areas of application namely military, under water, surveillance etc provides a wide opportunity of research.

V CONCLUSION

This paper presents a comprehensive overview of the impact and applications of CS in WSNs. A gist of the research developments and contributions made in data aggregation and recovery has been presented. Recent research on data aggregation based on adaptive sensing, distributed CS, sequential CS and other methodologies have been included. Data aggregation in large scale WSNs and its applications have also been presented. The impact of CS in routing, transmission, security, storage of WSN has also been discussed. Energy efficient and computationally competent algorithms for network routing and transmission have been presented. Research on encryption based on CS with an inherent advantage for security has revolutionized security in WSNs. An outline of CS based research contributions made in event detection, object localization and target detection in WSNs has also been detailed. The research challenges that are yet to be addressed effectively have been listed. The future directions required for researchers will definitely pave way for a CS based revolution in WSNs.

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