Adaptive Low Power Detection of Sparse Events in Wireless Sensor Networks

Ahmed S. Alwakeel*, Mohamed F. Abdelkader†, Karim G. Seddik‡ and Atef Ghuniem†
*Department of Communication and Electronics, Sinai University, Egypt
†Department of Electrical Engineering, Port Said University, Egypt
‡Electronics Engineering Department, American University in Cairo, Egypt
Email: en.aei@su.edu.eg, mdfarouk@eng.psu.edu.eg, kseddik@aucegypt.edu, atghuniem@yahoo.com

***Abstract*—Compressive Sensing (CS) has recently opened the door for efficient algorithms to solve various data gathering problems. Among these problems is sparse events detection in wireless sensor networks. In this problem, it is desirable to reduce the sensing cost by minimizing the number of sensors and the amount of data sent by each sensor. In this paper, we model the problem of sparse event detection as a compressive support recovery problem. We exploit the sparse and the binary nature of the event signal in the reconstruction algorithm using sequential compressive sensing. This provides an efficient solution to the problem, even under the assumptions of wide sensing area and high levels of noise. Simulation results show an improved performance under different compression ratios as compared to previous CS based approaches. It also shows the robustness of the proposed approach at low SNRs.**

I. Introduction

The last few years witnessed a dramatic growth for the need of Wireless Sensor Network (WSN), with increased emphasis on improving its performance. We can formulate the sensing problem in WSN as a data gathering problem, where the aim is to collect the data from the wireless sensors in a sink node with higher accuracy and lower power consumption. In WSN, power consumption occurs mostly due to the transmission process [1], thus researchers try to reduce the power consumed in wireless sensor either by reducing the amount of data sent by each sensor, reducing the number of sensors used to cover the target area, or both.

Many techniques were developed to address the problem of power consumption in WSN. Recently, Compressive Sensing [2]–[4] has gained an increased interest among these techniques. Through exploiting the sparse nature of most of the target signals, compressive sensing can reconstruct WSN data from a small number of linear measurements. Several variations of CS were used to address the problem, starting with [5] which models the problem in CS framework and reconstruct WSN data through linear projections of raw sensor readings. This was followed by modified versions of CS, which use coding compressive sensing [6] to code sensed data in order to decrease the amount of data. At the same time, another direction of research utilized CS to decrease the number of transmitting nodes rather than to decrease the amount of data [7]–[10].

Adaptive CS approaches have also seen several attempts in the WSN domain. In [8], the authors use adaptive CS to enhance the energy efficiency by adaptively collecting linear meaurments (projections) of the sensors data. A new projection vector is produced by the sink if it is not satisfied with the accuracy of the estimated data fields. Heuristic approaches are used for generating the projection vectors. A different adaptive approach was presented in [11], where at each time instant each sensor node decides randomly with a certain probability whether to transmit its measurement to the sink or not. In another approach, Chen *et. al.* [10] proposed to adaptively modify the sampling rate of each node, and CS is used to exploit the sparsity of the signal to reduce the sampling rate.

A special scenario occurs when the WSN is deployed to monitor an area for occurrence of rare events; this scenario occurs in several applications, such as alarm systems. In this case, the amount of data can be reduced by addressing the problem as a detection problem, where the target is to detect the occurrence of certain events. This can also be used as an initial stage in general WSN data gathering applications, followed by estimating the event values at the detected event location(s) [12].

In the event detection problem, the sparse nature of the sensed events opens the door for a different utilization of the CS theory as demonstrated in [13], where the authors use the channel matrix between the sensors and events as a measurement matrix and apply Bayesian compressive sensing (BCS) [14] to reconstruct the event vector. This approach was shown to achieve high performance at a much lower sampling rate than traditional CS approaches. However, the Bayesian compressive sensing is known to be sensitive to noise, which results in a degraded performance in low SNR scenarios such as wide WSN areas.

To overcome these limitations and further reduce the communication load even at low SNR, we propose to model the problem of event detection as a support recovery problem. We use the newly developed sequential compressive sensing (SCS) approach [12] to recover the support in an adaptive manner. The proposed approach assumes no prior knowledge about the noise statistics, and achieves high performance even at low SNRs. Our formulation allows for two levels of compression, which can reduce both the number of sensors needed and the amount of data transmitted to cover large areas within the WSN. Experimental results show that the proposed approach can achieve higher detection accuracy at a lower compression rate even in very noisy environment.

The rest of the paper is structured as follows. In Section II, we provide an overview of the mathematical background of CS and the different adaptive and non-adaptive reconstruction algorithms. The system model is described in Section III. In Section IV, we explain the proposed approach to apply SCS for support recovery in WSN. The experimental results are presented in Section V. We conclude with the conclusion and future work in Section VI.

II. A Mathematical Background on Compressive Sensing Algorithms

In this section, we briefly review the mathematical background of compressive sensing. Then, we describe the non-adaptive Bayesian Compressive Sensing. Finally, we discuss the Sequential Compressive Sensing algorithm that we use as an adaptive CS algorithm.

A. Compressive Sensing

Compressive sensing theory combines the signal acquisition and compression steps into a single step. The main requirement is that the acquired data is sparse in some transform domain, which means that the signal has a small number of non-zero element in that domain. CS theory proves that, under certain constraints on the measurement matrix, the acquired signal can be reconstructed from a small number of linear measurements [2], [3].

Consider a real-valued signal $\boldsymbol{x}_{N\times 1}$, which is sparse in some domain $\boldsymbol{\Psi}$.

$$\boldsymbol{x} = \sum_{i=1}^{N} s_i \boldsymbol{\psi_i} \quad \text{or} \quad \boldsymbol{x} = \boldsymbol{\Psi s}. \tag{1}$$

The signal $\boldsymbol{x}$ is K-sparse if it can be represented as a linear combination of only K basis vectors; that is, only K of the s_i coefficients in equation (1) are non zero.

In CS, we do not acquire $\boldsymbol{x}$ directly but rather acquire $M < N$ linear measurements $\boldsymbol{y}$, using an $M \times N$ measurement matrix $\boldsymbol{\Phi}$, as shown in the following equation.

$$\boldsymbol{y} = \boldsymbol{\Phi x} = \boldsymbol{\Phi \Psi s} = \boldsymbol{\Theta s}. \tag{2}$$

This linear system of equations is underdetermined since $M < N$, and hence it is impossible to uniquely recover $\boldsymbol{x}$ from $\boldsymbol{y}$. However, if the additional assumption that the vector $\boldsymbol{x}$ is K-sparse is imposed, where $K << N$, then the CS theory allows us to reconstruct the signal, provided that the measurement matrix $\boldsymbol{\Phi}$ satisfies a condition called the Restricted Isometric Property (RIP) condition [2].

The signal reconstruction problem is formulated as an ℓ_1-norm minimization problem.

$$\underset{\boldsymbol{s}\in\mathbb{R}^N}{min} \; ||\boldsymbol{s}||_{\ell 1} \quad \text{s.t.} \quad \boldsymbol{y} = \boldsymbol{\Phi \Psi s}. \tag{3}$$

This problem can be efficiently solved using linear programming techniques or greedy algorithms. However, in order to reconstruct the signal we need a number of measurement M that satisfies the condition:

$$M \geq C\mu^2(\Phi, \Psi) k \log N \tag{4}$$

where C is a small constant, and $\mu(\boldsymbol{\Phi}, \boldsymbol{\Psi})$ is the incoherence between the two matrices $\boldsymbol{\Phi}$ and $\boldsymbol{\Psi}$.

B. Bayesian Compressive Sensing

Bayesian compressive sensing (BCS) [14] is a probabilistic CS reconstruction algorithm that introduces a set of hyper-parameters which is considered as a prior over the sensed signal. The most probable values are iteratively estimated from the received data. In the binary event detction problem, the binary nature of event signals is used as a prior, which makes BCS more efficient than other traditional CS recovery algorithms like the ℓ_1-norm algorithm [13].

BCS converts the CS problem to a linear regression problem. The sparse vector $\boldsymbol{s}$ in equation (2) is represented as the summation of two N-dimensional vectors of the form $\boldsymbol{s} = \boldsymbol{s_l} + \boldsymbol{s_s}$, where $\boldsymbol{s_l}$ contains the M largest magnitude elements in $\boldsymbol{s}$, and the remaining $N-M$ elements in $\boldsymbol{s_l}$ are set to zero. Similarly, $\boldsymbol{s_s}$ contains the $N-M$ smallest magnitude elements in $\boldsymbol{s}$, and all the remaining elements in $\boldsymbol{s_s}$ are set to zero. Equation (2) can be reformulated as

$$\boldsymbol{y} = \boldsymbol{\Theta s} = \boldsymbol{\Theta s_l} + \boldsymbol{\Theta s_s} = \boldsymbol{\Theta s_l} + \boldsymbol{n_s} \tag{5}$$

where $\boldsymbol{n_s} = \boldsymbol{\Theta s_s}$ can be modeled as a zero-mean Gaussian noise with variance σ^2. We therefore have the Gaussian likelihood model

$$P\left(\boldsymbol{y}|\boldsymbol{\Theta}, \sigma^2\right) = \left(2\pi\sigma^2\right)^{-M/2} \exp\left(-\frac{1}{2\sigma^2}||\boldsymbol{y} - \boldsymbol{\Theta s_l}||^2\right). \tag{6}$$

We may assume a zero-mean Gaussian prior distribution over the signal $\boldsymbol{s}$ as

$$P(\boldsymbol{s}|\boldsymbol{\beta}) = \prod_{i=1}^{N} \mathcal{N}(\boldsymbol{s_i}|0, \beta_i^{-1})$$

where $\boldsymbol{\beta} = [\beta_1, \beta_2, \cdots, \beta_N]^T$ is a vector of N independent hyper-parameters.

The posterior parameter distribution conditioned over the signal is given by combining the likelihood and prior using Bayes rule:

$$P(\boldsymbol{s}|\boldsymbol{y}, \boldsymbol{\beta}, \sigma^2) = \frac{P(\boldsymbol{y}|\boldsymbol{s}, \sigma^2)P(\boldsymbol{s}|\boldsymbol{\beta})}{P(\boldsymbol{y}|\boldsymbol{\beta}, \sigma^2)} \tag{7}$$

which is a Gaussian distribution with mean μ and covariance Σ of the form

$$\mu = \sigma^{-2}\Sigma\boldsymbol{\Theta^T y}, \Sigma = (\boldsymbol{A} + \sigma^{-2}\boldsymbol{\Theta^T \Theta})^{-1} \tag{8}$$

where $\boldsymbol{A} = \mathbf{diag}(\beta_1, \cdots, \beta_N)$ is a diagonal matrix.

C. Sequential Compressive Sensing

Sequential Compressive Sensing [12] is a recent variation of CS that is referred to as adaptive compressive sensing. Similar to the distilled Sensing [15], the sparse signal is acquired through several adaptively designed measurement matrices. This allows for the sensing resources to be non-uniformly allocated in order to focus the sensing energy toward the non zero elements of the signal, allowing the signal to be efficiently reconstructed at lower SNRs [16], [17].

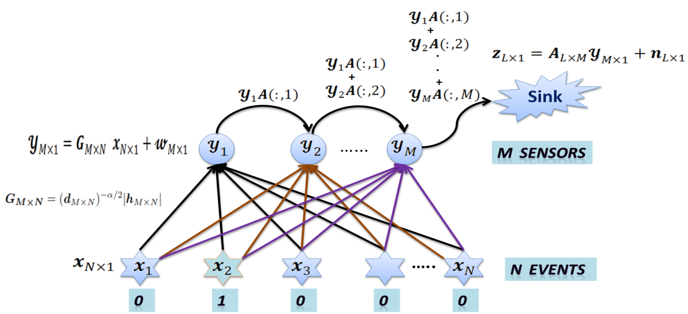

Fig. 1: System model of event detection in WSN.

At each iteration, an $M \times N$ measurement matrix $\boldsymbol{\Phi_t}$ is designed, where each column of this matrix has a single non-zero entry. The locations of these elements are randomly chosen according to a uniform distribution, while the amplitude of each non zero entry is selected randomly from $\{+\alpha, -\alpha\}$, where $\alpha > 0$.

The measurement matrix $\boldsymbol{\Phi_t}$ is used to collect M linear measurements. The measurement vector $\boldsymbol{y_t}$ can be represented as

$$\boldsymbol{y_t} = \boldsymbol{\Phi}_t \boldsymbol{x} + \boldsymbol{w_t} \tag{9}$$

where $\boldsymbol{w_t}$ is an $M \times 1$ vector of additive Gaussian noise.

The measurement vector is used to form the back-projected vector $\tilde{\boldsymbol{x}}_t$ by the relation

$$\tilde{\boldsymbol{x}}_t = \boldsymbol{\Phi}_t^T \boldsymbol{y}_t. \tag{10}$$

This process is repeated for t_1 iterations, where $t_1 = \log \frac{2}{\delta} + \log K + \log \log_2 \log M$, and $\delta > 0$ is the desired confidence parameter [12].

These back-projected vectors are combined to form a *signal proxy* $\hat{\boldsymbol{x}}$, with entries $\hat{\boldsymbol{x}}_i = \sum_{t=1}^{t_1} sgn(\tilde{\boldsymbol{x}}_{i,t})$. The support of the non zero elements is refined to include elements corresponding to $\hat{\boldsymbol{x}}_i < 0$. The corresponding columns of the measurement matrix are masked out for all following steps.

The above SCS algorithm is repeated for $\log_2 \log N$ steps. Each step removes, in expectation, half of the zero components while guaranteeing that all the non-zero components are retained with large probability. Thus, the expected number of components remaining after that is bounded by $N/\log N + K$, and the K non-zero components are guaranteed to be contained in this set [12].

III. SYSTEM MODEL

We consider a WSN of M sensors, deployed to monitor N binary event sources, where $M < N$ and both the sensors and event sources are randomly distributed in the sensing area. We denote the event signal as $\boldsymbol{x_{N\times1}}$, where $\boldsymbol{x} \in \{0, 1\}$. We assume that only a small portion of the sources $K << N$ are simultaneously active at any given instant of time. The sensors collect measurement data, and then send it to a sink node to detect the active events.

Similar to [13], the received signal vector at the sensors is represented as

$$\boldsymbol{y} = \boldsymbol{G}\boldsymbol{x} + \boldsymbol{w} \tag{11}$$

where $\boldsymbol{w}$ is the $M \times 1$ thermal measurement noise vector at the sensors, whose components are independent with zero mean and a variance of $\boldsymbol{\sigma_w^2}$, and $\boldsymbol{G}$ is the $M \times N$ Rayleigh fading channel matrix, whose elements are given by

$$G_{m,n} = d_{m,n}^{-\alpha/2} |h_{m,n}| \tag{12}$$

where $d_{m,n}$ is the distance between the n^{th} source and m^{th} sensor, α is the propagation loss, and $h_{m,n}$ is the Rayleigh fading (modeled as complex Gaussian random variable with zero mean and unit variance). Similar to [13], we assume that the sink has full knowledge of the channel state information matrix $\boldsymbol{G}$.

In order to reduce communication load, we consider a single-hop data gathering similar to [5], which distributes the consumed power equally among sensors in order to avoid high power consumption at end sensors. The sink node generates a measurement matrix $\boldsymbol{A}_{L\times M}$, where $L << M$, and sends it to all sensors. Each sensor multiples its reading $\boldsymbol{y}_i$ by the corresponding column of the measurement matrix. Then each sensor sends L readings to its neighbour sensor, and so on till the combined measurements reach the sink as shown in Figure 1. The $L \times 1$ received signal at the sink node can be written as

$$\boldsymbol{z} = \boldsymbol{A}\boldsymbol{y} + \boldsymbol{n} \tag{13}$$

where $\boldsymbol{n}$ is the additive noise vector at the sink, which has components that are independent with zero mean and a variance of $\boldsymbol{\sigma_n^2}$.

Our goal is to reconstruct the original event signal $\boldsymbol{x}_{N\times1}$ from the compressed received signal at sink $\boldsymbol{z}_{L\times1}$, where $K < L < M << N$.

IV. SEQUENTIAL COMPRESSIVE SENSING EVENT DETECTION

In this section, we model the problem in equation (13) as a support recovery problem and apply SCS to reconstruct $\boldsymbol{x}_{N\times1}$ from $\boldsymbol{z}_{L\times1}$, which are related as follows.

$$\begin{aligned} \boldsymbol{z} &= \boldsymbol{A}\boldsymbol{y} + \boldsymbol{n} \\ &= \boldsymbol{A}\boldsymbol{G}\boldsymbol{x} + \boldsymbol{A}\boldsymbol{w} + \boldsymbol{n} \\ &= \boldsymbol{A}\boldsymbol{G}\boldsymbol{x} + \boldsymbol{e} \end{aligned} \tag{14}$$

where $\boldsymbol{e}$ is the total $L \times 1$ combined noise in the system between event sources and the sink node.

As shown in section II-C, adaptive CS algorithms, such as SCS, depend on recovering the support of the sparse signal in an iterative manner, where the signal is captured at each iteration with different specially designed measurement matrices $\boldsymbol{\Phi}_t, t = 1, 2, \cdots, t_1$. We assume that the status of the event sources does not change during the acquisition process. Our problem formulation in equation (14) allows us a complete control over the measurement matrix $\boldsymbol{A}_{L\times M}$ between the sensors and sink node. Unfortunately this is not true for the measurement matrix $\boldsymbol{G}_{M\times N}$, which depends on the channel condition between the event sources and sensors, and hence cannot be altered.

This challenge can be avoided by noting that $M < N$, and assuming full knowledge of the channel response matrix $\boldsymbol{G}_{M\times N}$. Hence, the desired measurement matrix $\boldsymbol{A}_{L\times M}$ can be computed as

$$\boldsymbol{A}_t = \boldsymbol{\Phi}_t \boldsymbol{G}^{\dagger}, \tag{15}$$

where $\boldsymbol{G}^{\dagger}$ refers to the the pseudo-inverse of the $M \times N$ matrix $\boldsymbol{G}$. This pseudo-inverse can be efficiently computed using the singular value decomposition (SVD) of $\boldsymbol{G} = \boldsymbol{U}\boldsymbol{D}\boldsymbol{V}^T$, as follows.

$$\boldsymbol{G}^{\dagger} = \boldsymbol{V}\boldsymbol{D}^{-1}\boldsymbol{U}^T,$$

where $\boldsymbol{U}$ and $\boldsymbol{V}$ are orthonormal matrices, the superscript (T) denotes the transpose, and D is a diagonal matrix containing only the positive singular values of $\boldsymbol{G}$.

At each iteration, the sink node generates the measurement matrix $\boldsymbol{A}_t$ according to equation (15) and sends it to all sensors. Each sensor multiples its reading with the corresponding column in the measurement matrix and sends it back to sink using the single-hop model described. With this special design of the measurment matrix, the signal received at the sink at each step can be represented as

$$\boldsymbol{z}_t = \boldsymbol{A}_t \boldsymbol{y} = \boldsymbol{A}_t \boldsymbol{G}\boldsymbol{x} = \boldsymbol{\Phi}_t \boldsymbol{x}. \tag{16}$$

The back-projected vector $\tilde{\boldsymbol{x}}_{\boldsymbol{t}}$ can be calculated at the sink node as

$$\begin{aligned}
\tilde{\boldsymbol{x}}_{\boldsymbol{t}} &= \boldsymbol{\Phi}_t^T \boldsymbol{z}_t \\
&= (\boldsymbol{A}_t\boldsymbol{G})^T \boldsymbol{z}_t \\
&= (\boldsymbol{A}_t\boldsymbol{G})^T (\boldsymbol{A}_t\boldsymbol{G})\boldsymbol{x} + (\boldsymbol{A}_t\boldsymbol{G})^T \boldsymbol{e} \\
&= \boldsymbol{G}^T \boldsymbol{A}_t^T \boldsymbol{A}_t \boldsymbol{G}\boldsymbol{x} + (\boldsymbol{A}_t\boldsymbol{G})^T \boldsymbol{e}.
\end{aligned} \tag{17}$$

The back-projected vectors are combined to form *signal proxy* $\hat{\boldsymbol{x}}$, which is used to refine the support set. This process iterates a number of times to refine the search space and detect the active events correctly. The complete sensing process is illustrated in Figure 2. We note that most of the computation steps in this process are performed at the sink node, which generally has less stringent power constraints in wide area WSN.

The main benefit of the proposed approach is that it provides an effective way to recover the active events with fewer number of measurements, even under large noise levels. This can be attributed to the fact that SCS reduces the dimension of the search space and iteratively allocates the sensing energy to the more likely active events. This gives an advantage for adaptive design in event detection problem. As for non-adaptive designs, the amplitude of the smallest non-zero element of $\boldsymbol{x}$ must exceed $C_1\sqrt{\frac{N}{M}\sigma^2 \log N}$, where C_1 is a constant, M/N is the sensing energy per dimension, and $\sqrt{\log N}$ is needed to ensure that the signal is larger than the maximum noise contribution [18], [19]. However, the adaptive designs succeed under the weaker requirement that the amplitude of the smallest non-zero element of $\boldsymbol{x}$ exceeds $C_2\sqrt{\frac{N}{M}\sigma^2(\log K + \log\log_2 \log N)}$ where C_2 is a constant [12]. This results in an improved performance for larger number of events N, with fewer number of simultaneously active events $K << N$.

To make a fair comparison between SCS and BCS, we need to investigate the effect of our approach on other important parameters of the sensor network such as processing and communication load overhead. In BCS, each sensor multiplies the acquired signal of the sensor by a vector of length L representing a single column of the measurement matrix, and then transmits these L measurements. This process is repeated in SCS for $t_1 \times (\log\log_2 N)$ iterations. This may look like an excess overhead on the WSN resources. However, the length of the measurement vector L in each iteration in SCS can be significantly reduced. The experimental results in the following section show that we can achieve an improved detection performance for a much lower communication and processing overheads.

V. Simulation Results and Analysis

In order to show the effectiveness of our proposed approach, we evaluated, through simulation, the performance of the proposed sequential compressive sensing in event detection problem, and compared the performance to the Bayesian compressive sensing [14]. The simulated model consists of $N = 1000$ random sources randomly distributed in an area of 1000×1000 meters, with a minimum distance of $10m$ between any event and sensor. We randomly chose $K = 10$ events to be simultaneously active at any instant of time. We collect these events using $M = 500$ randomly distributed sensors over the sensed area. We averaged over 100 trials to avoid fluctuation.

We compare the performance of the SCS and the BCS algorithms at different SNRs and compression ratios. Since we model the problem as a detection problem, we use the Probability of Correct Detection (PCD) and the Probability of False Alarm (PFA) as our performance metrics, where PCD refers to the percentage of correctly recovered active events and PFA refers to the percentage of non-active events that are falsely detected as active.

The compression ratio in our experiment represents the ratio between the total amount of data sent and the number of event sources. In the original work using BCS [13], compression ratio was considered as the ratio between the number of sensors and number of events. In our simulation, we fix the number of sensors M and change the compression ratio by changing the number of measurements transmitted by each sensor, L. We take into consideration the iterative nature of SCS, which requires the sensors to send multiple times, as described in section IV. Thus, the compression ratio in SCS is calculated as $\left(\frac{L\times t_1 \times \log\log_2 N}{N}\right)$.

In Fig. 3, we show the probability of correct detection of our proposed SCS algorithm and BCS plotted against the compression ratio, evaluated at different SNR values. This figure shows that SCS achieves a comparable detection rate

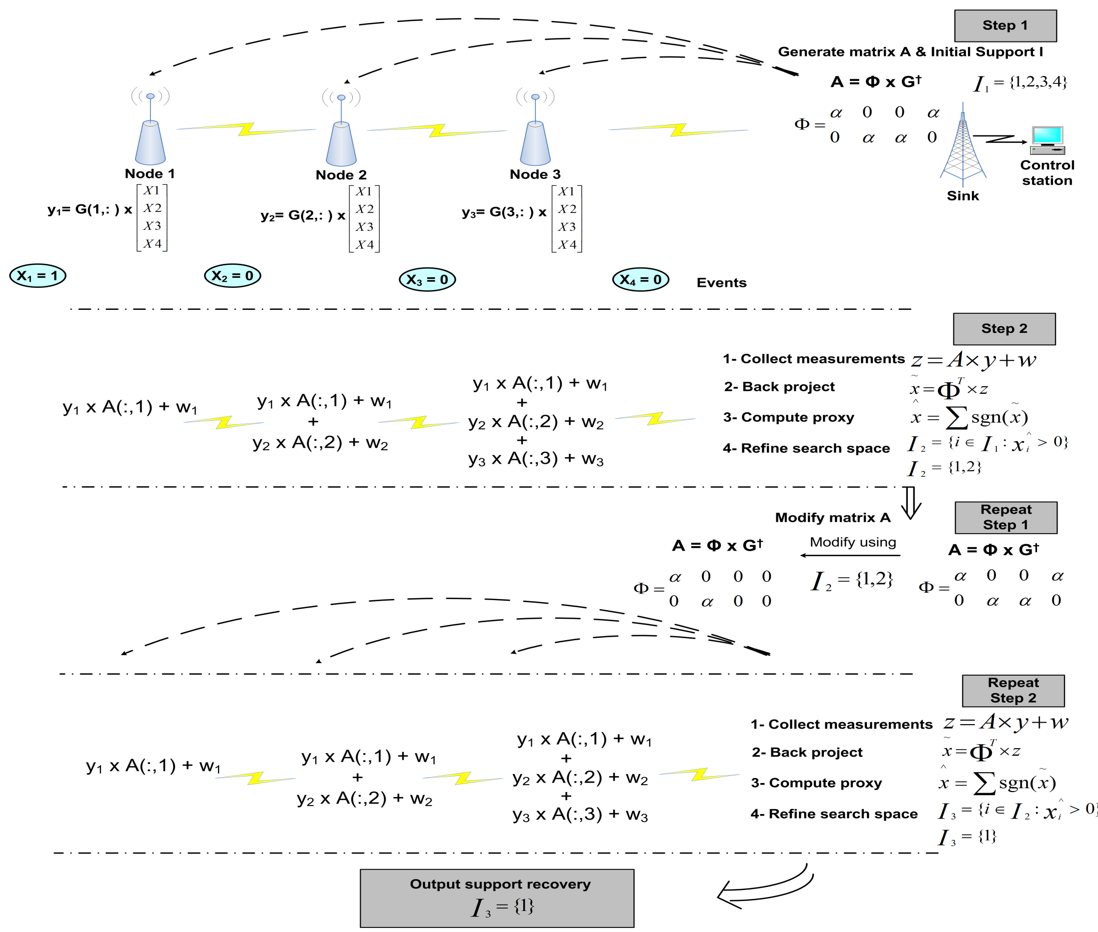

Fig. 2: Model for applying Sequential Compressive Sensing in WSN.

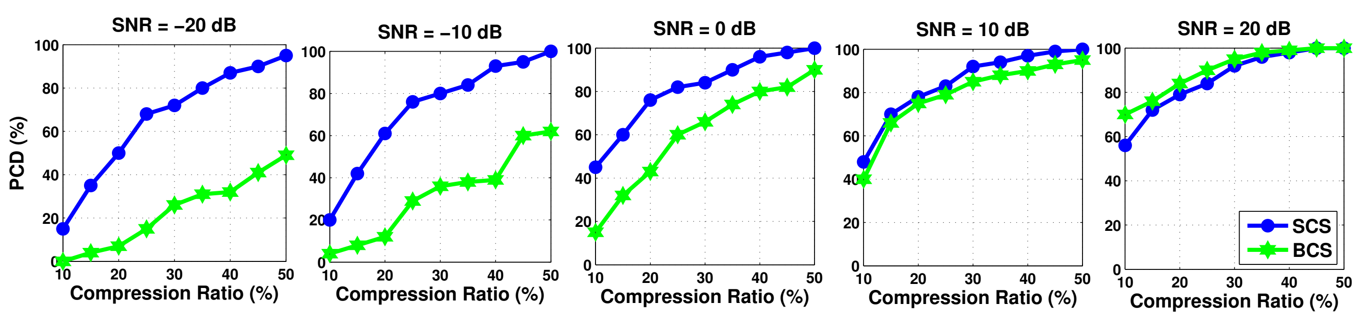

Fig. 3: Probability of Correct Detection (PCD) vs. Compression Ratio at different SNR levels.

at high SNR values (20dB). However, as the noise level increases, BCS performance deteriorates while SCS performance remains consistent across different noise levels. This noise immunity of SCS is more evident in Figure 4, which shows the probability of false alarm (PFA) against the compression ratio at different SNR values. This is theoretically justified by the fact that PFA in SCS depends only on the number of iteration steps instead of the noise levels. The same behaviour, but from another perspective, is shown in Figure 5 and Figure 6, which show PCD and PFA against the SNR at different compression ratio values.

VI. Conclusion

In this paper, we formulate events detection problem in Wireless Sensor Networks as a compressive support recovery problem. Exploiting the binary nature of the events signals, we utilize a recent adaptive CS algorithm called Sequential Compressive Sensing, which gives an advantage in low SNR scenarios that are common in wide area WSN. We show through simulations that the proposed approach can lead to a higher probability of correct detection and lower probability of false alarm as compared to non-adaptive reconstruction

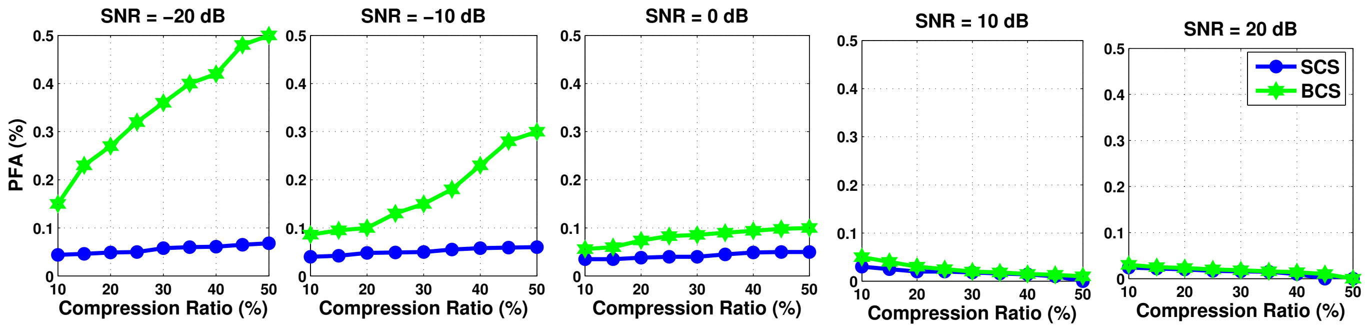

Fig. 4: Probability of False Alarm (PFA) vs. Compression Ratio at different SNR levels.

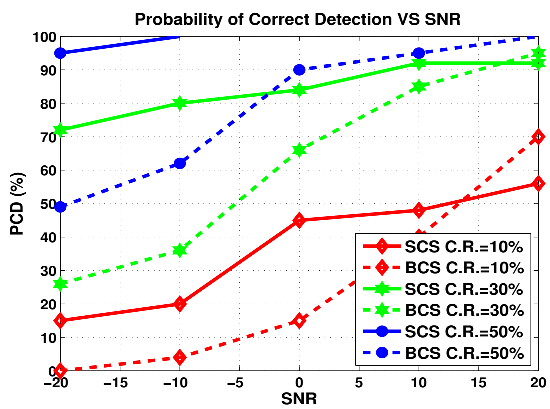

Fig. 5: Probability of Correct Detection vs. SNR at different Compression Ratios.

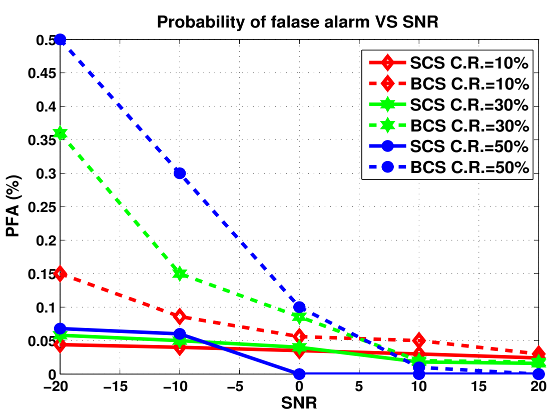

Fig. 6: Probability of False Alarm vs. SNR at different Compression Ratios.

algorithms, especially under high noise levels.

References

[1] M. Balouchestani, K. Raahemifar, and S. Krishnan, "Compressed sensing in wireless sensor networks: Survey," *Canadian Journal on Multimedia and Wireless Networks*, vol. 2, no. 1, pp. 1–4, 2011.

[2] D. Donoho, "Compressed sensing," *Information Theory, IEEE Transactions on*, vol. 52, no. 4, pp. 1289–1306, 2006.

[3] R. Baraniuk, "Compressive sensing [lecture notes]," *Signal Processing Magazine, IEEE*, vol. 24, no. 4, pp. 118–121, 2007.

[4] E. Candes and M. Wakin, "An introduction to compressive sampling," *Signal Processing Magazine, IEEE*, vol. 25, no. 2, pp. 21–30, 2008.

[5] C. Luo, F. Wu, J. Sun, and C. W. Chen, "Compressive data gathering for large-scale wireless sensor networks," *ACM, Proceedings of the 15th Annual International Conference on Mobile Computing and Networking*, pp. 145–156, 2009.

[6] N. Nguyen, D. Jones, and S. Krishnamurthy, "Netcompress: Coupling network coding and compressed sensing for efficient data communication in wireless sensor networks," *Signal Processing Systems (SIPS), 2010 IEEE Workshop on*, pp. 356–361, 2010.

[7] S. Lee, S. Pattem, M. Sathiamoorthy, B. Krishnamachari, and A. Ortega, "Compressed sensing and routing in multi-hop networks," *University of Southern California CENG Technical Report*, 2009.

[8] C. T. Chou, R. Rana, and W. Hu, "Energy efficient information collection in wireless sensor networks using adaptive compressive sensing," *Local Computer Networks, 2009. LCN 2009. IEEE 34th Conference on*, pp. 443–450, 2009.

[9] Q. Ling and Z. Tian, "Decentralized sparse signal recovery for compressive sleeping wireless sensor networks," *Signal Processing, IEEE Transactions on*, vol. 58, no. 7, pp. 3816–3827, 2010.

[10] W. Chen and I. Wassell, "Energy efficient signal acquisition via compressive sensing in wireless sensor networks," *Wireless and Pervasive Computing (ISWPC), 2011 6th International Symposium on*, pp. 1–6, 2011.

[11] G. Quer, R. Masiero, G. Pillonetto, M. Rossi, and M. Zorzi, "Sensing, compression, and recovery for wsns: Sparse signal modeling and monitoring framework," *Wireless Communications, IEEE Transactions on*, vol. 11, no. 10, pp. 3447–3461, Oct. 2012.

[12] J. Haupt, R. Baraniuk, R. Castro, and R. Nowak, "Sequentially designed compressed sensing," *Statistical Signal Processing Workshop (SSP), 2012 IEEE*, pp. 401–404, 2012.

[13] J. Meng, H. Li, and Z. Han, "Sparse event detection in wireless sensor networks using compressive sensing," *Information Sciences and Systems, 2009. CISS 2009. 43rd Annual Conference on*, pp. 181–185, 2009.

[14] S. Ji, Y. Xue, and L. Carin, "Bayesian compressive sensing," *Signal Processing, IEEE Transactions on*, vol. 56, no. 6, pp. 2346–2356, 2008.

[15] J. Haupt, R. Castro, and R. Nowak, "Distilled sensing: Adaptive sampling for sparse detection and estimation," *Information Theory, IEEE Transactions on*, vol. 57, no. 9, pp. 6222–6235, 2011.

[16] J. Haupt, R. Baraniuk, R. Castro, and R. Nowak, "Compressive distilled sensing: Sparse recovery using adaptivity in compressive measurements," *ignals, Systems and Computers, 2009 Conference Record of the Forty-Third Asilomar Conference on*, pp. 1551–1555, 2009.

[17] M. Iwen and A. Tewfik, "Adaptive strategies for target detection and localization in noisy environments," *Signal Processing, IEEE Transactions on*, vol. 60, no. 5, pp. 2344–2353, 2012.

[18] M. Wainwright, "Sharp thresholds for high-dimensional and noisy sparsity recovery using ℓ_1 -constrained quadratic programming (lasso)," *Information Theory, IEEE Transactions on*, vol. 55, no. 5, pp. 2183–2202, 2009.

[19] S. Aeron, V. Saligrama, and M. Zhao, "Information theoretic bounds for compressed sensing," *Information Theory, IEEE Transactions on*, vol. 56, no. 10, pp. 5111–5130, 2010.