Robust Wireless Sensor Networks with Compressed Sensing Theory

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ABSTRACT: *Wireless Sensor Networks (WSNs) consist of a large number of Wireless Nodes (WNs) each with sensing, processing, communication and power supply units to monitor the real-world environment information. The WSNs are responsible to sense, collect, process and transmit information such as pressure, temperature, position, flow, vibration, force, humidity, pollutants and biomedical signals like heart-rate and blood pressure. The ideal WSNs are networked to consume very limited power and are capable of fast data acquisition. The problems associated with WSNs are limited processing capability, low storage capacity, limited energy and global traffic. Also, WSNs have a finite life dependent upon initial power supply capacity and duty cycle. The WSNs are usually driven by a battery. Therefore, the primary limiting factor for the lifetime of a WN is the power supply. That is why; each WN must be designed to manage its local power supply of energy in order to maximize total network lifetime [5]. The life expectancy of a WSN for a given battery capacity can be enhanced by minimizing power consumption during the operation of the network. The CS theory solves the aforementioned problem by reducing the sampling rate throughout the network. A combination of CS theory to WSNs is the optimal solution for achieving the networks with low-sampling rate and low-power consumption. Our simulation results show that sampling rate can reduce to 30% and power consumption to 40% without sacrificing performances by employing the CS theory to WSNs. This paper presents a novel sampling approach using compressive sensing methods to WSNs. First, an overview of compressed sensing is presented. Second, CS in WSNs is investigated. Third, the simulation results on the sampling rate in WSNs are shown.*

Keywords: Wireless Sensor Network, Sampling-rate, Power consumption, Sparse signals, Compressed sensing

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1. Introduction

Wireless Sensor Networks (WSNs) consist of a large number of Wireless Nodes (WNs) each with sensing, processing, communication, and power supply units to monitor and control the information of real environments. As a communication system, in the WSNs, sources are WNs, which measure some quantity; the channel is the space between the WNs and receiver which is another WN or Base Station (BS). The WSNs are now used in a variety of fields such as health monitoring in designing Electronic Health (EH), transportation automation in designing Traffic Control System (TCS), industrial control monitoring in designing Web Controlling System (ISC), business and residential areas in designing Energy Management System (EMS), and military for providing Electronic War Systems (EWS). The WSNs suffer of some problems like limited processing capability, low storage capacity, limited energy, and high sampling rate. The compressive sensing that also known as compressed sensing is a revolutionary idea proposed recently to achieve much lower sampling rate for sparse signals such as biomedical signals, WSN's signals, and signals of Wireless Body Area Networks(WBAN's) [5]. By compressing data, the data size is reduced, and less bandwidth is required to transmit data: therefore, less power is required to process the data. The CS helps in data gathering and transferring and can change the traditional theorem and technology in wireless networks, which may lead to some other improvements in capacity, delay, size, and energy management [4]. This theory says a small number of random linear measurements of compressible signals contain enough information for reconstruction, processing, and communication [8]. To extend WSNs to many areas including: health monitoring, home automation, control monitoring, military, transportation automation, and energy management, a combination of the CS theory to WSNs is the best solution for designing autonomous networks with low sampling-rate, low-power, self-organizing and self-maintenance[6]. The aim of this paper is to investigate how CS theory can be employed in WSNs to design a robust network with low-sampling rate and low-power consumption. The structure of this paper is organized as follows: Section 2 presents a background about the CS theory. Section 3 investigates the CS theory to WSNs. Section 4 the simulation result on sampling-rate and power consumption in WSNs is shown. Finally, the conclusion is drawn in Section 5.

2. Overview of Compressed Sensing Theory

The CS theory is emerging for such WSNs by compressing, the date size reduced, and fewer bandwidth is required to transmit data and therefore less power is required to process data[9]. This theory says a small number of random linear measurements of compressible signals contain enough information to recover the original signal [10]. This idea attracts many talented researchers on areas like Information Communication Technology (ICT), Random Variables (RVs), Optimization Procedures (OPs) and Mathematical Statistics (MSs) [8]. A basic block diagram of the CS scheme is provided in Figure 1.

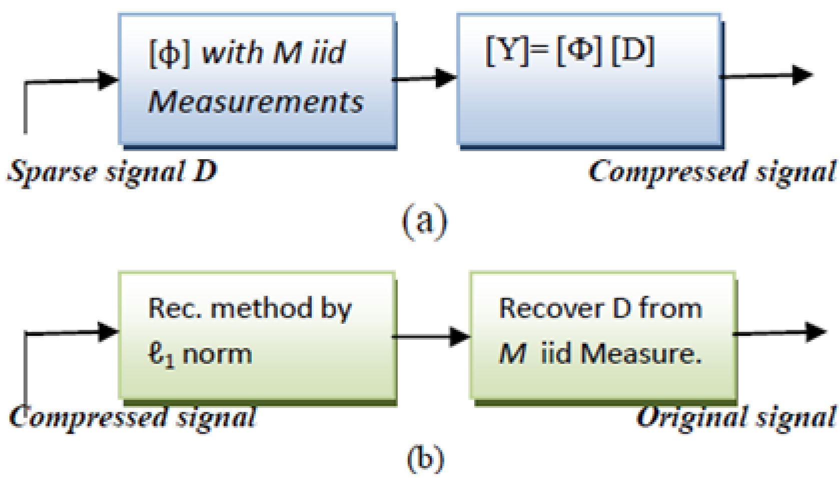

Figure 1. a) CSin transmitter b) CS in receiver

The CS theory exploits that many natural signals such as WSNs's signals are sparse or compressible in sense that they have concise representations when expressed in the proper basis[1]. With CS theory,WSNs can achieve a higher transmission rate, a lower time delay, and high probability of success of data transmission. In this section, we first, discuss the CS theorem. Second, the reconstruction method to recover the original signal in the receiver side is investigated.

2.1. Basic Theorem

Regarding the Nyquist theory, each signal must be sampled at least twice its bandwidth in order to be represented without error. Our goal in the CS theory as a new sampling scheme is to reduce load of sampling rate. The CS theory says many signals are sparse or in the practice near sparse and can represent by small number of random measurements [11]. Any compressible signal D in $\mathbb{R}^N$ can be expressed in terms of a basis of $N \times 1$ vectors $\{\psi_i\}$ such that $1 \leq i \leq N$. Forming the $N \times N$ basis matrix $\Psi = [\psi_1, \psi_2, \ldots\ldots, \psi_N]$ by stacking the vector ${}_i$} as columns, the compressible signal D including K non-zero and (N-K) zero coefficients can be represented like [12]:

$$D = \sum_{i=1}^{N} S_i \psi_i \quad \text{or} \quad [D]_{N\times 1} = [\Psi]_{N\times N}[S]_{N\times 1} \tag{1}$$

Where S is the $N \times 1$ column vector of weighting coefficients $S_i = \langle D, \psi_i \rangle = \psi_i^T D$. Therefore any compressible signals D can be represented of an orthogonal basis of $N \times 1$ vector $\psi_i\}$. On the other hand, any compressible signal has a small number of large coefficients and a lot of number of small coefficients [13]. That is why any compressible or sparse signal has K nonzero coefficients and (N-K) zero coefficients with $K \ll N$. In fact, the CS theory offers a stable measurements metrics with M independent and identically distributed (i.i.d) elements of the compressed signals such as $K \leq M \ll N$ .Therefore the compressed signal $\mathbb{Y}$ is found like:

$$[\mathbb{Y}]_{M\times 1} = [\phi]_{M\times N}[D]_{N\times 1} \tag{2}$$

By substituting (2) in (1) we have [13]:

$$[\phi]_{M\times N}[\Psi]_{N\times N}[S]_{N\times 1} = [\Theta]_{M\times N}[S]_{N\times 1} \tag{3}$$

Thus CS scenario has two steps. First, offers a stable measurement matrix that ensures that the salient information in any compressible signal is not damaged by the dimensionality reduction from $D \in \mathbb{R}^N$ down to $\mathbb{Y} \in \mathbb{R}^M$. In the second step, the CS theory offers a reconstruction algorithm under certain condition and enough accuracy to recover original signal D from compressed signal. Fortunately, the $[\phi]_{M\times N}$ matrix has the following interesting properties:

- The $[\phi]_{M\times N}$ matrix is incoherent with the orthogonal basis with high probability and enough accuracy
- The $[\Theta]_{M\times N} = [\phi]_{M\times N}[\Psi]_{N\times N}$ matrix is also i.i.d Gaussian for every possible Ψ.
- The $[\Theta]_{M\times N} = [\phi]_{M\times N}[\Psi]_{N\times N}$ matrix has the RIP with high probability if (the number of random measurements) M verifies the following equation:

$$M \geq cK \log(N/M) \tag{4}$$

where c is a small constant. As the result, CS theory focus on few number of linear combination of all points of the signal instead of huge number of samples to find compressed signal with matrix ϕ. Selecting the measurement y_j into $M \times 1$ vector $\mathbb{Y}$ and the measurement vector ϕ_j^T to rows into an $M \times N$ matrix ϕ we can write:

$$\begin{pmatrix} y_1 \\ y_M \end{pmatrix} = \begin{pmatrix} \phi_{11} & \cdots & \\ \vdots & \ddots & \vdots \\ & \cdots & \phi_{M\times N} \end{pmatrix} \begin{pmatrix} d_1 \\ d_N \end{pmatrix} \tag{5}$$

2.2 Reconstruction Scheme

The compressed sensing theory provides the guarantee that a compressible signal can be fully describe by only M random measurements. Consequently, we can recover the original signal D from the compressed signal with only M random measurements with high probability and enough accuracy. Our goal is to find the signal's sparse coefficient vector S in the translated null space. Therefore, the reconstruction method needs only M random measurements of random matrices ϕ ,Ψ to recover the original signal [1].

We define the ℓ_p norm of the vectors s as $(\| S \|_p)^p = \sum_{i=1}^{N} |S|^p$. When $p=0$ we obtain the ℓ_0 "*norm*" that counts the number of non-zero coefficients in S; hence a K-sparse vector has ℓ_0 norm K. The main procedure to solve inverse problem in ℓ_2 norms is by least squares that shows ℓ_2 minimizations will almost never find the data vector D, and also solving ℓ_0 is numerically unstable method. That is why; the ℓ_0 and ℓ_2 minimizations are not convenient to recover original signal from the compressed signal but fortunately we can exactly reconstruct the original signal by ℓ_1 norm with high probability and enough accuracy [3]. To summarize, the CS theory offers a reconstruction mechanism to recover original signal D from the compressed signal Y with high probability and enough accuracy with only M random linear measurements [22]. Therefore, we can expect to recover the original signal D with high probability from just $M \geq cKlog \ll (N/M) \ll N$ random Gaussian measurements. We also thank to the properties of the i.i.d Gaussian distribution to make Gaussian measurements ϕ which are universal to generate $\Theta = \phi\Psi$ which has the RIP with high probability.

3. WSNs with CS Theory

This section presents the basic theory of WSNs, and then we investigate how compressed sensing could improve the limiting characteristics such as power and delay in wireless nodes. The WSNs consist of important units such as sensing unit (SU), power supply unit (PS), communication and controlling unit (CC). The important concept of WSNs is based on a simple equation like:

$$\text{PS} + \text{SU} + \text{CC} = \textit{Thousands of potential applications} \qquad (6)$$

In this part, we want to investigate how to employ the CS theory in WSNs, which mostly involve data of a large number of WNs. Typically; in WSNs we have the following properties:

- There are a total of *N* sources randomly located in a filed
- We denote *K* as the number of event that active sources generate to be measured
- *K* is a random number and is much smaller than *N*
- We denote $[D]_{N\times1}$ as the event vector
- Each component of $[D]_{N\times1}$ has a binary value
- Obviously $[D]_{N\times1}$ is a sparse vector since $k<<N$
- There are *M* active monitoring wireless sensors trying to capture *K* events
- The number of events *K*, the number of wireless sensors *M* and total of sources *N* has the following relation: $(K \leq M<<N)$

Also in WSNs we have:

- Very limited number of active wireless sensors compared with total of wireless sensors
- Very limited number of events compared to the number of sources
- Thus, the events are relatively sparse compared to the number of sources

Therefore, we can say data vectors in WSNs are sparse vectors and consequently CS theory can employ to WSNs [3]. A WSN with *N* sources, each node acquiring a sample *Di*. The final goal is to collect Data vector $D = [D_1, D_{2\ldots\ldots}, D_N]$. D has an *M*-Sparse in a proper basis like:

$$\Psi = [\Psi_1, \Psi_2 \ldots \Psi_N] \qquad (7)$$

CS suggests that, under certain condition, instead of collecting *D* we can collect compressed vector $Y = \Phi D$, where $\Phi = \{\Phi_{ji}\}$ is $K\times N$ sensing Matrix whose entries are i.i.d random variables. In non-CS WSNs with *N* nodes a node is receiving *N*-1 packets and send out *N* packets (*N*-1) received packets plus its data) each packet corresponding to data sample from a node and the BS needs to receive all *N* samples [21]. In WSNs with CS theory the BS needs only to receive *M* ($M \approx K$) packets. Obviously, in order to use CS, each node needs to know the value of Compressed Ratio ($CR = N/K$) that is constant and known and value of *N*. The node *i* computes $K = N/CR$ and generate *K* values Φ_{ji} $(1 \leq j \leq k)$ and create a vector like:

$$D_i[\Phi_{1i}, \Phi_{2i}, \ldots\ldots\ldots\ldots, \Phi_{ki}] \qquad (8)$$

where D_i is its own data. Typically, node *i* will wait to receive from all its downstream neighbors. Each received packet carries its *index from* 1 *to K* so that it can *be added to the data already waiting in i with the same index* (either locally produced or received from a neighbor). Then node *i* will send exactly *K-Packets* corresponding to the aggregated column vectors. Finally, compressed vector *Y* is generated like:

$$\begin{pmatrix} Y_1 \\ \vdots \\ Y_M \end{pmatrix} = \begin{pmatrix} \phi_{11} & \ldots & \phi_{1N} \\ \vdots & \vdots & \vdots \\ \phi_{M1} & \ldots & \phi_{MN} \end{pmatrix} \begin{pmatrix} D_1 \\ \vdots \\ D_N \end{pmatrix} \qquad (9)$$

Now the different between CS and non-CS operation becomes clear: CS operation requires each node send exactly *M* packets irrespective of what it has receive and each node needs to know *CR* and *N* and then computes value of ($M \approx K$). The received vector in Base Station (BS) can be Witten as:

$$[Y]_{M\times1} = [\Phi]_{M\times N}[D]_{N\times1} + \varepsilon_{M\times1} \qquad (10)$$

where $[Y]_{M\times1}$ is compressed data vector that is received by BS and $\varepsilon_{M\times1}$ is the thermal noise vector whose components are independent and has zero mean and unit variance. Consequently, the received vectors in BS are an condensed representation of the sparse events.

3.1 Two Important Questions

The first question is that, whether or not the information of *K-Sparse* signal is damaged by the dimensionally reduction from *N* bits of information to *M* bits of information [20]. Surprisingly the information is not damaged because of the *D* vector of date is the sparse vector. If *D* is not sparse enough, as long as $M \leq N$, the signal is damaged since there are fewer equations than unknowns. The next question is how to develop a reconstruction algorithm to recover data vector from the compressed data vector *Y* under the certain condition and high probability [19]. We can recover data vector *D*, by solving a convex optimization via ℓ_1 norm. Our model shows in Figure 2. That is why; the compressed data can be generated from only *M* bits of information instead of *N* bits of information such as $M \approx K << N$ which *K* is the number of the events in WSNs [18]. Regarding the explanation above, we can apply the CS theory to WSNs as a new sampling method to reduce sampling rate and power consumption.

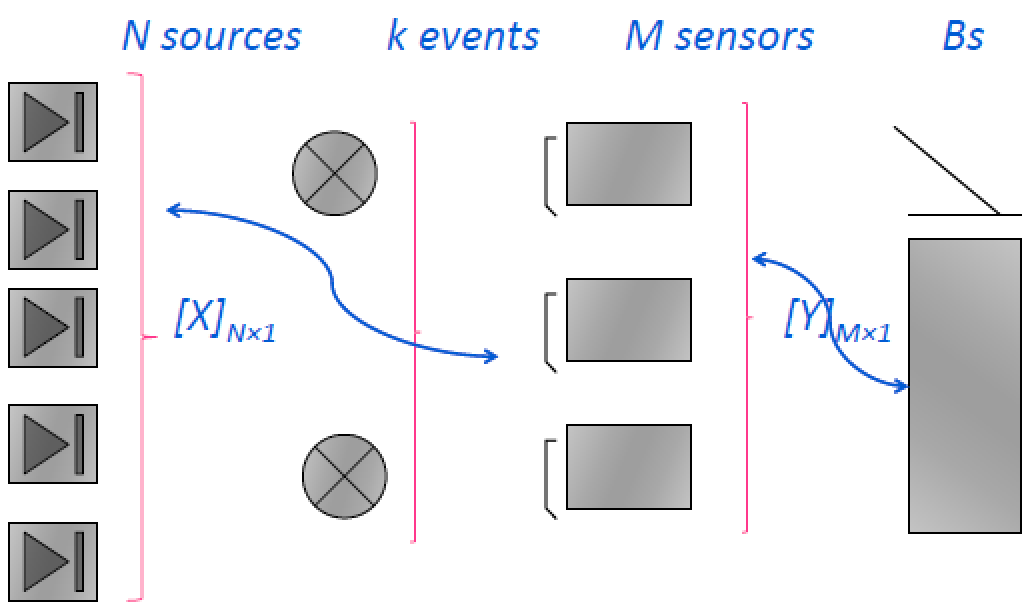

Figure 2. Sparse data vectors in WSNs

4. Simulation Results

Our simulation shows that the sampling rate in WSNs can reduce to 30% and power consumption to 40% without sacrificing performance and with further decreasing the sampling rate and power consumption, the performance is gradually reduced until 12% sampling rate and 15% power consumption. In this section, we fist, the simulation results on sampling-rate present. Second, the simulation results about power consumption are investigated.

4.1. Simulation Results on Sampling-Rate

To simulate sampling-rate, we have gotten some assumption to simulate sampling rate [2]. The important assumption is:

- N =100 (Total number of sources randomly located within 500m-by-500m area)
- *M* as the number of wireless nodes is also randomly located within this area

• Sampling Rate (*SR*) = *M / N*

• *K* as the number of random events which is a random and small number

• The propagation loss factor is very small

• The transmitted power is normalized to 1

• PDF of random variable is Gaussian

• $\varepsilon_{M\times 1}$ as the thermal noise is very small and can be discard

Our result shows, we can reduce sampling rate in SSWSNs until 30% without any problem in detection [4]. The following results are extracted:

• If sampling rate is higher than 30%, the detection probability is almost 100%

• The performance gradually reduces as the sampling rate reduces and as K (the number of events) increase

• $CR = N / K$ is increased when *K* is decreased

By increasing the number of events the accuracy of detection events decreased. Table 1 shows our simulation on sampling rate with different values for *K*.

Number of events	SR(Non-CS network)	SR(CS-based network)	Detection Probability
K ≤ 10	100%	25%	100%
10 ≤ K ≤ 25	100%	30%	100%
K ≥ 25	100%	35%	100%

Table1. Sampling rate reduction for different values of K

Figure 3 shows our simulation on sampling rate with Gaussian distribution and different values for K=5, K=10, K=50. In the non-CS scenario a wireless node is receiving *N*-1 packets (each packet corresponding to a data sample from a wireless node) and will send out *N* packets (the *N*-1 received packets plus its own data sample); the base station, in particular, will need to receive all the *N* packets. Now the difference between CS and non-CS operation becomes clear: CS operation requires each node in WSNs to send exactly *K* packets irrespective of what it has received. In non-CS networks each wireless node needs send *N* packets with *K*<<*N*. In the CS scenario by compressing, the data size is reduced and fewer bandwidths is required to transmit data and therefore, less power is required to process and transmit data[15]. Table 2 compares our simulation results with non-CS network [7].

Number of events	Sampling rate reduction	Detection Probability
K ≤ 10	**Until 25%**	100%
10 ≤ K ≤ 25	**Until 30%**	100%
K ≥ 25	**Until 35%**	100%

Table2. Simulation results for non-CS network and CS network

In some cases, the Uniform distribution works better than Gaussian distribution for random measurements. Figure 4 illustrates simulation sampling rate for WSNs.

4.2 Simulation Results on Power Consumption

An important key of any WSN is to minimize the power consumed by the units of WN such as PS, CU, and SU. That is why; power consumption can be divided into three domains: sensing, processing, and communication units. The power available in the WN is often restricted. It makes power optimization more complicated in WSNs. By applying the CS to WSNs the sleep time increases by decreasing the number of bits in communication and processing units. After increasing the sleep time, the power consumption should be minimized to extend the life of each WN. Our simulation results that show compressed sensing theory

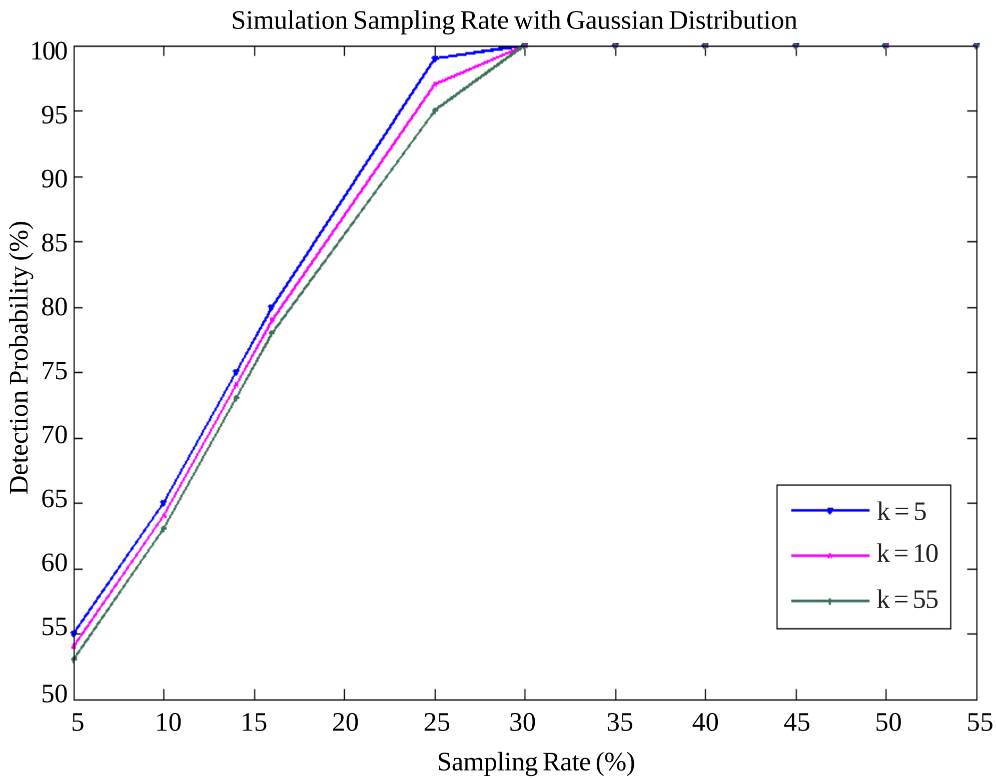

Figure 3. Sampling rate for K= 5, K = 10, K = 50 with Gaussian distribution

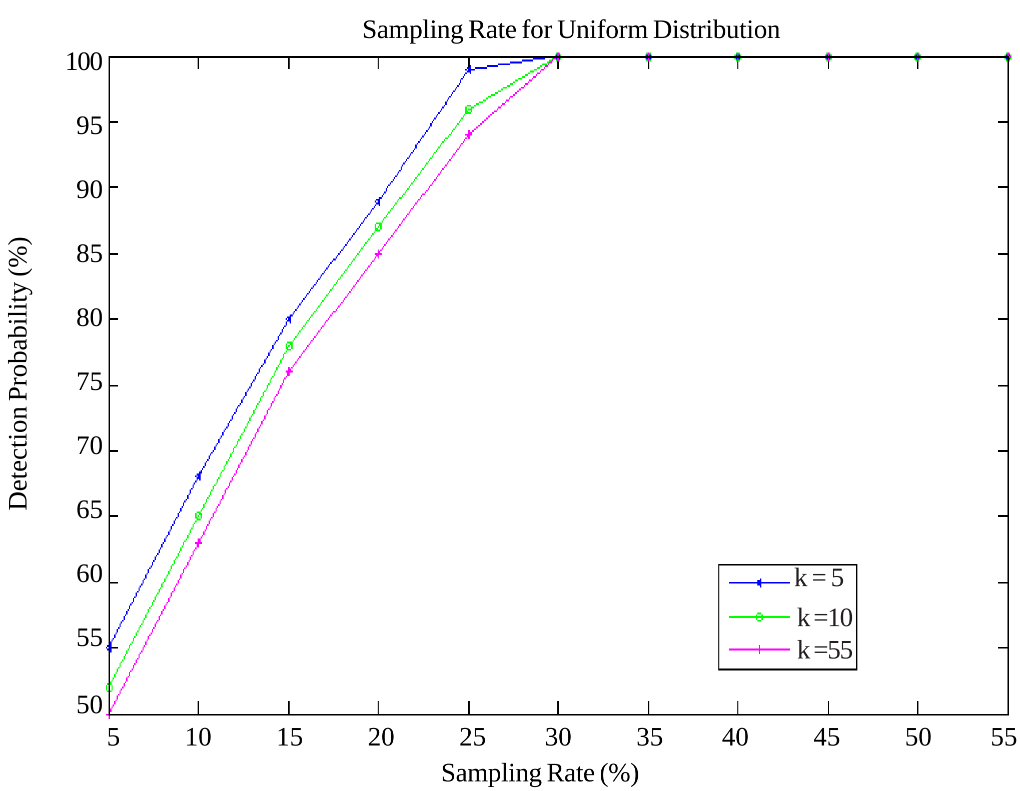

Figure 4. Sampling rate for K = 5, K = 10, K = 50 with Uniform distribution

as a new sampling method in WSNs are beneficial in reducing the total of power consumption [6]. The simulation results are produced using the simulator developed C^{++} and MATLAB. In this simulation we use some assumption including [14]:

- Number of WNs are 100
- WNs are uniformly distributed in the area about 2000 × 2000 m
- The power supply of each WN has a 15 Jules for CU, PU and SU
- The effective rate for communication unit of each WN is 200m
- The simulation time is 825 seconds
- Power consumption for communication unit in sending mode is 550 mw and in receiving mode is 25 mw
- Each WN consume 9 milliamps in active mode and 5 μA in sleep mode
- Bandwidth for WSN is 1.5 Mb / s
- Each WN has enough time for sending its data to BS
- Simulation packet size 1500
- Simulation interval is 150
- Network topology is star
- The data of WNs are driven form a uniform distribution between 1 and 200
- compressed sensing has N=100 and M=10

Figure 5 shows the power consumption in term of Compressed Ratio (CR) in small scale of WSNs with 100 wireless nodes [16].

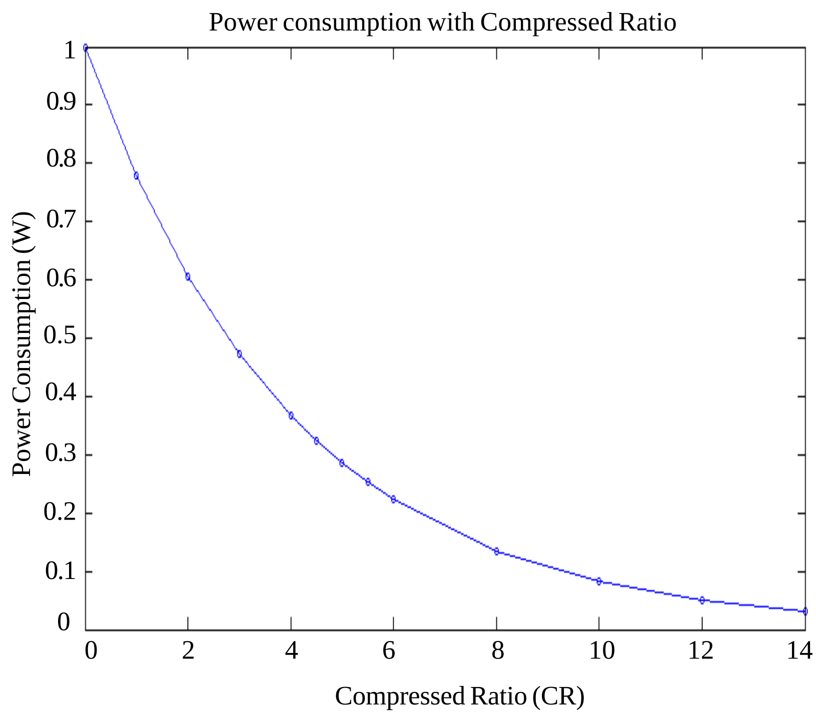

Figure 5. Simulation of power consumption

Figure 6 shows simulation results on power consumption in term of Compressed Ratio ($CR = N/M$) for three signals with N = 1024, N = 2048, N = 3072 and Gaussian distribution in WBANs.

The results of simulation are shown in Table 3 and compared in WSN with CS and without CS theory.

The final simulation results on sampling rate and power consumption are summarized in Table 4. It is evident that CS as a new sampling scheme can minimize low of sampling rate and power consumption in WSNs.

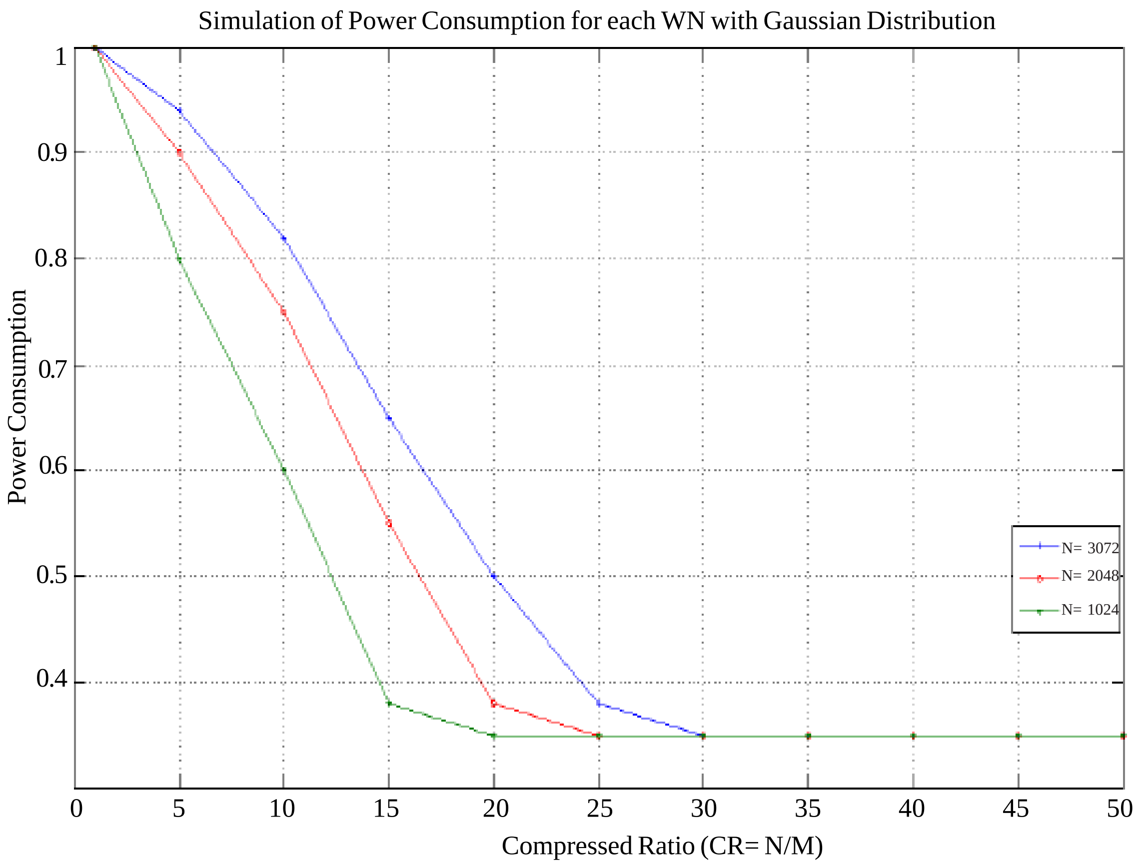

Figure 6. Simulation results on power consumption in term of Compressed Ratio

Parameter	Without CS with N=100	With CS with M=10
Power cons. in CU	600 mw	110 mw
Power cons. in SU	200 mw	90 mw
Power cons. in PU	180 mw	80 mw

Table 3. Results of power consumption

5. Conclusion

In this research proposal, we have investigated the benefit of applying the CS theory to data collection in the WSNs. We first described how to employ the CS theory to WSNs for achieving low sampling-rate and power consumption. Second, we formulated the requirements to apply the CS theory in WSNs. We also employed the CS theory to the WSNs to design low sampling-rate and power consumption network in order to design robust networks with low power consumption. From the simulation results, we investigated that sampling-rate in WSNs can reduce to 30% and power consumption to 40% without sacrificing performances.

6. Further Works

We have investigated how to employ the CS theory in WSNs. It will be part of our future work to provide a general scheme of the CS to any WSNs. We are also going to develop the CS theory to reduce power consumption to provide low-power WSNs

Numbaer of measurements (M)	Number of samples N=1024	Number of samples N=2048	Number of samples N=3072
100	CR=10.24 SR → 27% PC → 33%	CR=20.24 SR → 27% PC → 33%	CR=30.72 SR → 27% PC → 33%
200	CR=5.12 SR → 29% PC → 35%	CR=10.24 SR → 29% PC → 35%	CR=15.36 SR → 29% PC → 35%
300	CR=3.41 SR → 37% PC → 39%	CR= SR → 37% PC → 39%	CR= SR → 37% PC → 39%
400	CR=2.24 SR → 42% PC → 41%	CR= SR → 42% PC → 41%	CR= SR → 42% PC → 41%

Table 4. Simulation results on sampling rate and power consumption

with more than 100 WNs. We also want to apply the CS theory to reduce sampling-rate in large scale WSNs with more than 100 WNs.

References

[1] Balouchestani, M., Raahemifar, K., Krishnan, S. (2011). Increasing the reliability of wireless sensor network with a new testing approach based on compressed sensing theory, *In:* Wireless and Optical Communications Networks (WOCN), 2011 IEEE International Conference on Wireless Sensor Networks, p. 1-4, May.
[2] Aeron, S., Saligrama, V., Manqi Zhao, (2010). Information Theoretic Bounds for Compressed Sensing, *IEEE Transactions on Information Theory*, 56, 5111-5130.
[3] Mohammadreza Balouchestani, Kaamran Raahemifar, Sridhar Krishnan , (2011). Power Management of Wireless Sensor Networks with Compressed Sensing Theory, 16th IEEE International Conference on Networks and Optical Communications and 6th Conference on Optical Cabling and Infrastructure (OC&I 2011) Northumbria University, Newcastle upon Tyne, UK, p. 122-125, July.
[4] Zhuang Xiaoyan, Wang Houjun, Dai Zhijian, (2010). Wireless sensor networks based on compressed sensing, *In:* Computer Science and Information Technology (ICCSIT), 2010 3rd IEEE International Conference on, p. 90-92.
[5] Beutel, J., Dyer, M., Lim, R., Plessl, C., Wohrle, M., Yucel, M., Thiele, L. (2007). Automated wireless sensor network testing, *In:* Networked Sensing Systems, 2007. INSS '07. Fourth International Conference on, p. 303-303.
[6] Choi, K., Wang, J., Zhu, L., Suh, T. S., Boyd, S., Xing, L. (2010). Compressed sensing based cone-beam computed tomography reconstruction with a first-order method, Med. Phys., 37, p. 5113-5125, Sep.
[7] Mohammadreza Balouchestani, Kaamran Raahemifar, Sridhar Krishnan, (2011). Low-Power wireless Sensor Networks with Compressed Sensing theory, *In:* Fly-By-Wireless(FBW2011),Montreal,Quebec, IEEE Xplore, p.1-4, July.
[8] Chang, C. H., Ji, J. (2010). Compressed sensing MRI with multichannel data using multicore processors, Magn. Reson. Med., 64, p. 1135-1139, Oct.
[9] Doneva, M., Bornert, P., Eggers, H., Stehning, C., Senegas, J., Mertins, A. (2010). Compressed sensing reconstruction for magnetic resonance parameter mapping, Magn. Reson. Med., 64, p. 1114-1120, Oct.
[10] Donoho, D. L. (2006). Compressed sensing, *IEEE Transactions on Information Theory*, 52, p. 1289-1306.
[11] Haupt, J., Bajwa, W. U., Rabbat, M., Nowak, R. (2008). Compressed Sensing for Networked Data, *IEEE Signal Processing Magazine*, 25, 92-101.
[12] Luo, J., Xiang, L., Rosenberg, C. (2010). Does compressed sensing improve the throughput of wireless sensor networks? *In:* Communications (ICC), 2010 IEEE International Conference on, p. 1-6.

[13] Wang, H., Miao, Y., Zhou, K., Yu, Y., Bao, S., He, Q., Dai, Y., Xuan, S. Y., Tarabishy, B., Ye, Y., Hu, J. (2010). Feasibility of high temporal resolution breast DCE-MRI using compressed sensing theory, Med. Phys., 37, 4971-4981, Sep.
[14] Mohammadreza Balouchestani, Kaamran Raahemifar, Sridhar Krishnan, (2011). Power Management of Wireless Sensor Networks with Compressed Sensing Theory, 16th IEEE International Conference on Networks and Optical Communications and 6th Conference on Optical Cabling and Infrastructure (OC&I 2011) Northumbria University, Newcastle upon Tyne, UK, p. 122-125, July.
[15] Al-Karaki, J. N., Kamal, A. E. (2004). Routing techniques in wireless sensor networks: a survey, *IEEE Wireless Communications*, 11, 6-28.
[16] Capella, J. V., Bonastre, A., Ors, R., Peris, M. (2010). A Wireless Sensor Network approach for distributed in-line chemical analysis of water, *Talanta*, 80, 1789-1798, Mar 15.
[17] Mohammadreza Balouchestani, Kaamran Raahemifar, Sridhar Krishnan, (2011). Compressed Sensing in Wireless Sensor Networks: Surway, *Canadian Journal on Multimedia and Wireless Networks*, 2 (1) 1-4, February.
[18] Jia Meng, Husheng Li, Zhu Han, (2009). Sparse event detection in wireless sensor networks using compressive sensing, *In*: Information Sciences and Systems, 2009. CISS 2009. 43rd Annual Conference on, p. 181-185.
[19] Keong, H. C., Yuce, M. R. (2009). Analysis of a multi-access scheme and asynchronous transmit-only UWB for wireless body area networks, Conf. Proc. *IEEE Eng. Med. Biol. Soc*., p. 6906-6909.
[20] Ko, J., Gao, T., Rothman, R., Terzis, A. (2010). Wireless sensing systems in clinical environments: improving the efficiency of the patient monitoring process, *IEEE Eng. Med. Biol. Mag*., 29, 103-109, Mar-Apr.
[21] Mohammadreza Balouchestani, Kaamran Raahemifar, Sridhar Krishnan, (2011). Concepts for Designing Low-Power Wireless Sensor Networks with Compressed Sensing Theory, 2011 International Conference on Communication and Broadband Networking (ICCBN 2011)), Kuala Lumpur, Malaysia, p. 47-51, June.
[21] Halder, A., Bhattacharya, S., Chatterjee, A. (2008). System-Level Specification Testing Of Wireless Transceivers, Very Large Scale Integration , IEEE Transactions on VLSI Systems, 16, 263-276.
[22] Chun Tung Chou, Rana, R., Wen Hu, (2009). Energy efficient information collection in wireless sensor networks using adaptive compressive sensing, *In:* Local Computer Networks. LCN 2009. IEEE 34th Conference on 2009, p. 443-450.