# Compressed sensing in wireless sensor networks: Survey

**Article** · January 2011



Mohammadreza Balouchestani
Indiana University-Purdue University Fort Wayne


Sridhar Krishnan
M. S. Ramaiah College of Hotel Management

Canadian Journal on Multimedia and Wireless Networks Vol. 2, No. 1, February 2011

# COMPRESSED SENSING IN WIRELESS SENSOR NETWORKS: SURVEY

Mohammadreza Balouchestani, Kaamran Raahemifar, and Sridhar Krishnan

Department of Electrical and Computer Engineering
Ryerson University, Toronto, Canada
mbalouch@ee.ryerson.ca, kraahemi@ee.ryerson.ca, krishnan@ee.ryerson.ca

**Abstract-**Wireless Sensor Networks (WSNs) are adopted in many applications such as, industrial automation, military, transportation, environmental monitoring, web controlling, biomedical and energy management. As WSNs continue to grow, so does the need for new mechanisms to reduce parameters such as power consumption, cost, delay and traffic. The Compressed Sensing (CS) theory holds promising improvements to these parameters. The CS shows that sparse signals and information in WSNs can be exactly reconstructed from a small number of random linear measurements. This paper provides most recent survey of CS theory as it is applied in WSN. The mathematical basis of CS theory is discussed, and important parameters in WSN are described. We explore improvements in factors such as lifetime, delay, cost and power in WSNs.

**Keywords**: Compressed Sensing, Wireless Sensor Networks, Power consumption, Wireless Nodes.

## 1. INTRODUCTION

**W**ireless sensor networks consist of a large number of wireless nodes and are responsible for sensing, processing and monitoring environmental data [1]. The wireless nodes collect environmental data such as temperature, pressure, position, flow, humidity, vibration, force and motion to monitor the real-world. There are limiting parameters on WSNs such as power consumption, lifetime, delay, size, bandwidth, signal distortion and cost and global traffic. The WSNs also require independent energy resources and therefore, energy consumption is the most important factor to determine the lifetime of wireless sensors. The combination of CS theory with WSNs holds promising improvements to some of these limits [2]. The CS optimizes energy consumption which is an important factor in WSNs [3]. The CS states that sparse signal of information in WSNs can be exactly reconstructed from a small number of random linear measurements of information in WSNs [4].The CS provides a new approach to mathematical complexities especially where sparse information is applied. CS tends to recover data vector $\mathcal{X} \in R^N$ with $N$ number of information form data vector $\mathcal{Y} \in R^M$ with $M$ number of information such that $M \ll N$ [5]. In fact, CS offers a stable information matrix that does not depend in any way on the information signal $\mathcal{X}$ [6].Given the rapid emergence of CS topic and the lake of tutorial or review papers on its applications in promising fields such as WSNs this paper aims to provide a survey of selected topics of CS in WSNs.

This paper is organized as follows: In Section 2, the mathematical basis of CS theory is presented. In Section 3, WSNs and important limiting characteristics are discussed. In Section 4 the WSNs with traditional sampling method combined with the CS theory are discussed. Section 5 concludes the paper with some discussions about future work.

## 2. Compressed Sensing Background

CS is a new theory of sampling in many applications, including data network, sensor network, digital image and video camera, medical systems and analog-to-digital convertors [7]. CS also offers links between applied mathematics, information theory, data acquisition and optimization theory in advanced digital signal processing [8]. In fact, CS offers a new method of compression and coding, in order to minimize storage and cost. This revolutionary technique results in a smaller number of random linear projections of a compressible signal that contains sufficient information for approximation or exact reconstruction [9].

### 2.1. Compressed Sensing scenario

Any compressible signal $\mathcal{X} \in \mathbb{R}^N$ can be represented in the form of

$$\mathcal{X} = \sum_{J=1}^{N} S_J \psi_J \quad \text{Or} \quad \mathcal{X} = S\,\psi, \tag{1}$$

where $S$ demonstrates the $N \times 1$ column vector of coefficients such that

$$S_J = \psi^T \mathcal{X}. \tag{2}$$

$\mathcal{X}$ is in time domain and $S$ is in $\psi$ domain. The compressible signal $\mathcal{X}$ can be shown as a linear combination of K vectors with $K \ll N$, and $K$ nonzero coefficients and $N-K$ zero coefficients in Eq. (1). In many application signals have only a few large coefficients. These few large coefficients signals can be approximated by $K$ [10]. One would then select $K$ largest coefficients and discard $(N-K)$ smallest coefficients. Traditionally, one is required to acquire the full $N$-sample of signal $\mathcal{X}$ to compute the complete group of transform coefficients. The traditional compression techniques suffer from an important inherent inefficiency since it computes all $N$ coefficients and records all the nonzero, although $K \ll N$ [11]. The CS can replace the traditional sampling with new sampling scheme and reduce the number of measurements. In fact, CS combines acquisition step and compression step into one step and can directly acquire signals without going through the intermediate steps. As a result, a small number of coefficients can be transmitted or stored rather than the full set of signal coefficients. Consequently, CS provides a scheme that reduces power consumption, size and cost. The CS offers $M$ measurements with $(K < M \ll N)$ and enough information to reconstruct $\mathcal{X}$ [11]. The other transform matrix $\phi$ is used to obtain the compressed signal $\mathbb{y}$ :

$$\mathbb{y} = \phi\,\mathcal{X}. \tag{3}$$

Using Eq. (1), the compressed signal can be represented as:

$$\mathbb{y} = \phi\,\mathcal{X} = \phi\psi S = \Theta S, \tag{4}$$

where $\Theta$ is a $M \times N$ matrix and $\mathbb{y}$ is an $M \times 1$ vector. The measurement process for M is non-adaptive and hence, $\phi$ is independent on the signal $\mathcal{X}$. Since the measurement algorithm is linear and defined in terms of the matrices $\phi$ and $\psi$, solving for s given $\mathbb{y}$ in (4) is a linear algebraic method [12]. The CS offers a Gaussian random matrix $\phi$ as an independent and identically distributed (iid). $\phi$ is incoherent and $\Theta$ has the Restricted Isometry Property (RIP) with high probability if $M \leq c\ K\ log\ (N/K)$ such that $c$ is a small constant with $c > 0$. Therefore CS offers stable measurements matrix $\phi$ that does not depend in any way in the original signal. It also offers a reconstruction method to recover $\mathcal{X}$ from compressible signal $\mathbb{y}$ [2]. Reconstruction algorithm needs only M measurements to recover the original signal. CS transfers $\mathcal{X} \in \mathbb{R}^N$ to $\mathbb{y} \in \mathbb{R}^M$ [6].

### 2.2 Signal Recovery

According to the results, CS theory shows that sparse signals can be exactly reconstructed from a small number of linear measurements [4]. The CS theory illustrates that original signal can be fully described by the M measurements in $\mathbb{y}$ [13]._ It is possible to reconstruct K-sparse vectors with high probability via $\ell_1$ optimization as [13]:

$$s^{\wedge} = argmin \parallel s' \parallel_1 \text{ such that } \Theta s' = \mathbb{y}. \quad (5)$$

Clearly, the CS data acquisition algorithm considers random measurements based on $\phi$ followed by linear mechanism reconstruction to obtain original signal $\mathcal{X}$.

## 3. Wireless sensor network background

Wireless Sensor Network has opened the doors to many applications that need monitoring, processing and control. A WSN system is ideal for an application like environmental monitoring in which the requirements mandate a long-term deployed solution to acquire water, soil, or climate measurement. For utilities such as the electricity grid, streetlights, and water municipals, wireless sensors offer a lower-cost method for collecting system data to reduce energy usage and better manage resources [14]. WSN is used to effectively monitor highways, bridges, and tunnels. This section presents the basic theory of WSN and its limiting characteristics such as power and delay in wireless nodes.

### 3.1 Basic Techniques of Wireless Sensor Network

WSN consists of spatially distributed autonomous nodes that use sensors to monitor physical or environmental conditions [15]. Each wireless node has four main sections including sensing unit, processing unit, communication unit and an energy supply unit [16]. The wireless sensor nodes are usually deployed to acquire measurements such as temperature, pressure, flow, humidity, position and torque to the gateway. The gateway collects the measurement from each node and sends it over a wired connection, typically Ethernet, to a host controller. Wireless nodes in gateway sense information around their monitoring distance except the sink nodes in end layer that only get the information from other nodes and make decisions [16]. The amount of information that should be processed in a gateway is huge which causes global traffic. The CS promises to reduce the global traffic and to decrease data correlation. Thus, WSNs which apply CS techniques should require lower power. In the following subsections, the components of WSN nodes are discussed.

#### 3.1.1 Power Supply Unit

Power is a primary constraint in the wireless nodes and the power supply should provide power for sensing unit, communication unit, processing unit. This fundamental power constraint further limits everything from data sensing rates and bandwidth, to node size, cost, security and weight [17]. The power supply unit in most of the cases is a battery. The battery lifetime is related to the discharge rate or amount of current drawn. Therefore, the amount of information decreases when CS is used and the current drawn in power supply drops. It is anticipated that CS would extend the battery lifetime to more than current lifetime [18].

There is a focus on increasing the lifetimes of power supply through power management. This is all due to the fact that maintenance and replacement of power supply is expensive and difficult. Today, power management technologies in WSNs are constantly evolving due to extensive research. The primary limiting factor for the lifetime of a wireless node is the energy supply. Each node must be designed to manage its local supply energy in order to maximize total network lifetime [18].

A wireless node periodically wakes up to acquire and transmit data by powering and then it goes back to sleep mode to conserve energy [18]. If wireless node decides to switch to sleep mode in time $t_1$, the power consumption reduces to $P_{sleep}$with $\tau_{down}$ delay and if decides to go back to active mode, the power increase to $P_{active}$ with $\tau_{up}$ delay**.** The energy in sleep mode is as follows [18]:

$$E_{sleep} = \frac{\tau_{down}(P_{active}+P_{sleep})}{4} + (t_1 - \tau_{down})P_{sleep}. \quad (6)$$

The energy in active mode can be expressed as [38]:

$$E_{active} = \frac{\tau_{down}(P_{active}+P_{sleep})}{4} + (\tau_{down} - t_1)\, P_{active}\,. \quad (7)$$

Therefore the energy saving is:

$$E_{saved} = E_{active} - E_{sleep}. \quad (8)$$

As a result, in wireless nodes, switching to sleep mode is beneficial if $E_{overhead} < E_{saved}$ that $E_{overhead}$ is:

$$E_{overhead} = \frac{\tau_{up}(P_{active}+P_{sleep})}{2}. \quad (9)$$

As the bit length of the information decreases, the duration of sleep mode increases and consequently the consumption power decreases, currently a research interest in WSNs.

In a WSN the transmission power in active mode is given by [19]:

$$P_t \propto \frac{R^2}{N}\,, \quad (10)$$

where $N$ is the number of bits of information and R is distance between source and destination nodes.

The transmission rate in active mode can be represented like [19]:

$$T_r = \sqrt{\frac{\log N}{\pi N}}\,, \quad (11)$$

where $N$ is the bit length of information in WSNs. As $N$ decreases, the transmission power and transmission rate increase. This result is achieved by using CS in WSNs.

#### 3.1.2. Sensing unit

WSNs consist of lots of sensors which measure pressure, temperature, humidity, flow, position to monitor physical or the real-world environment conditions. The sensors are deployed randomly in the certain area and are correlative [13]. The wireless sensors are capable of sensing their environments, processing the information locally, and sending it to one or more collection points through a wireless link .There are some standards which govern the communication between the sensor nodes. The IEEE 1451 standard provides roles for wireless sensors to make it easier for different manufactures to develop sensors and interfaces to WSNs. The IEEE 802.11standard is designed for Wireless Local Area Network (WLAN) and provides data transfer between computers and other devices such as switches and routers. The data transfer rate is between 1 Mbps and 50 Mbps. The IEEE802.15.4 standard is designed for multiple data rates and multiple transmission frequencies [13]. The transmission frequencies in IEEE802.15.4 are 868 MHz, 902, 928 MHz, 2.48, 2.5 GHz and data rates are 20kbps, 40kbps and 250 kbps. This standard supports peer-to-peer wireless network and specifies optional use to encryption of transmitted data. As a result, the IEEE802.15.4 can be adopted in a large scale WSNs where compressed nodes work with CS theory

[16]. These standards are very flexible in nodes with sleep, active and idle modes.

### 3.1.3. Processing Unit

The Processing unit consist of microcontroller or microprocessor, memory, interfaces, counters and timers. Regarding the application of WSNs, the processing unit has many types of microcontrollers or microprocessors from 4 to 64 bits. The 64-bit microcontrollers have three states or modes: sleep, idle, active modes. They support different power consumption in each mode.

In the active mode, a clock is also still running, which can be used for scheduled wake ups, when the microcontroller switches to other modes. As a result, the consumption is decreased, and the battery lifetime is increased. The power consumption in microcontrollers is as follows [19]:

$$\mathrm{P} \quad \alpha \quad f v^2. \qquad (12)$$

Eq. (12) states that power consumption P depends on voltage $v$ and frequency $f$.

The active mode consumption power is approximately 10 times more than sleep mode. Longer sleep mode is the best way to reduce power consumption of microcontrollers. One can anticipate longer sleep mode with CS since the CS decreases the number of information and consequently the sleep mode time will increase. Subsequently, the power consumption in microcontroller should be decreased if CS is used.

### 3.1.4. Communication unit

The wireless nodes must communicate with themselves and other sensors. The communication unit consists of transmitter and receiver. One of the important factors in communication unit is power consumption. The communication unit usually has the largest power consumption in wireless sensors. There are factors in communication units such as communication rate, transmit and receive power and type of modulation which govern the power consumption.

There are three methods to communicate: data network, acoustic communication, optical communication and Radio Frequency (RF). Acoustic communication uses a kind of transducer to transmit data encoded as sound waves in WSN. The power consumption in these systems is low but the size of the transducer limits its applications [18]. Optical communication systems are based on a laser beam to send data in WSN. They can be categorized as optical active systems or optical passive systems. The optical passive system does not produce its own laser on board. It has a micro-electromechanical system corner-cube-reflector (MEMS CCR) to reflect or scatter the laser from the source. It requires an external device to generate the beam and then receive and decode the data of nodes. Active optical systems combine the laser beam generator on board and a message is transmitted by the laser to encode data. The active optical is not transmitted in all directions, but it is focused with a small divergence.

In the third communication method, RF systems, nodes communicate with themselves and other nodes via radio frequency and use the IEEE 802.11 protocol. The transmitter power $P_T$ in RF system is as follows [17]:

$$\Psi = \frac{P_T}{4\pi R^2}, \qquad (13)$$

where $\Psi$ is power density and $P_T$ is transmitter power and R is the distance from the nodes. Noisy environment may create a problem for receivers to detect data from noise. In that case, optical or acoustic communication needs to be considered rather than RF system.

The communication units usually can work in four states including sleep mode, operation mode, transmit or receive mode and idle mode [17]. The sleep mode has lower power than other modes. Thus it is important to change to sleep mode, when it is not transmitting or receiving data. The power consumption in communication unit depends on SNR (Signal to Noise Ratio) and BER (Bit Error Rate). Consequently, with CS signal noise and bit error rates and power consumption should be decreased [18].

## 4. Compressed Sensing in Wireless sensor Networks

In this section the application and advantages of the CS theory in WSNs is studied and the implications on lower power consumption, lower time delay, higher probability of data transmission, reducing traffic, energy management and cost [18] are discussed.

### 4.1. Wireless Sensor without Compressed Sensing

A WSN consists of a large number of nodes with small devices each with sensing, processing, communication and controlling abilities to monitor the real environment. A WSN with *N* nodes, each having information or data $x_i$, $i$=1, 2, 3….*N*. Each $x_i$ has a scalar value and therefore network data is arranged in a vector as [18]:

$$\mathcal{X} = [x_1, x_2, \ldots, x_n]^T. \qquad (14)$$

As mentioned in Section 2, one is required to acquire the full N-samples of signal $\mathcal{X}$ to compute the complete group of transform coefficients although *K*<<*N*. (*K* is nonzero coefficients of information). The network data vector $\mathcal{X}$ is very large and it is a problem of processing in a WSN with thousands or millions of nodes.

### 4.2. Wireless Senor Networks with compressed sensing

The CS can reduce the number of information in WSNs [19]. Suppose *X* has *K*-Sparse representation if there is a convenient basis like:

$$\psi = [\psi_1, \psi_2, \ldots, \psi_k]^T. \qquad (15)$$

Then network data vector is demonstrated like [7]:

$$\mathcal{X} = \sum_{i=1}^{N} S_i \, \psi_i. \text{ Or } \mathcal{X} = S\,\psi. \qquad (16)$$

In WSNs there are *K* coefficients among these *N* nodes with $S_i$ information that are nonzero with $K \ll N$. The current compression methods need to process all *N* coefficients where *N* is usually a large number to find the location of nonzero coefficients [19]. CS offers a new sampling model by acquiring compressed information without computing the coefficients. It is possible to offer *M* information in WSNs $K<M\ll N$ and enough information to reconstruct the original information [18]. Thus, information in data networks could be reduced from *N* to *M* and transmit *M* data and save memory space. CS offers a stable information matrix $\phi$ and suggests that instead of collecting $\mathcal{X}$, compressible network data vector $\mathcal{Y}$ can be collected and $\mathcal{Y}$ is given by [19]:

$$\mathcal{Y} = \phi\mathcal{X} = \phi\,\psi\,S, \qquad (17)$$

such that $\phi = \{\phi_{j,i}\}$ is a sensing matrix with inputs i.i.d uniformly distributed random variable with variance $1/_M$ [20]. Consequently, the compressed data vector $\mathcal{Y}$ has a far less information and it is much easier to store, transmit and process. Mathematically (17) is transformed to:

$$\begin{pmatrix} y_1 \\ \vdots \\ y_m \end{pmatrix} = \begin{pmatrix} \phi_{11} & \phi_{12} & \phi_{13} \\ . & . & . \\ \phi_{m1} & . & \phi_{mn} \end{pmatrix} \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix}. \qquad (18)$$

The suitable value for M is given by [14]:

$$M \leq \frac{K \log^{N}/_{K}}{^{1}/_{C}}, \tag{19}$$

where $c$ is small constant [18]. Four conditions have to be met to recover information X from the information Y. First, in WSNs with N nodes, R is defined as a common rate for all nodes and should guarantee that [19]:

$$R \geq \sqrt{\frac{logN}{\pi N}} . \tag{20}$$

Second, the arrival rate $\lambda$ should be [19]:

$$\lambda \leq \frac{4WN}{\sigma MlogN} \tag{21}$$

where $w$ is the bandwidth and $\sigma > 0$ is some small constant. Third, the serving rate $\mu$ in WSN from each node to another node must be guaranteed as [20]:

$$\mu = \frac{1+W\lambda}{W}. \tag{22}$$

Fourth, consider a network with N nodes, where node $n_i$ sends information to node $n_j$. To successfully transmit data, the distance between $n_i$and $n_j$ should not be greater than the common rate R and is given in [20]:

$$\|n_i - n_j\| \leq R. \tag{23}$$

Node $n_k$ transmits information to $n_j$ node. The distance between them should be greater than the common rate R. Otherwise, they cannot communicate well.

## 5. CONCLUSION

This paper described how effective CS theory can be if applied in WSNs. It discussed two key features, new sampling method for information and data networks and new recovering method. This paper re-emphasized the benefits of the CS in WSNs. We have shown CS holds promising improvements to limiting characteristics of WSNs such as power consumption, life time, traffic and time delay. We have discussed the limitations of CS in WSNs. As our future research, we intend to apply CS in WSNs with biomedical WSNs in mind. Also the CS technique which works for a given WSN might not be adapted for another WSN with different requirements. Our future objective is to simulate a CS method which can be adaptable to more than one WSN.

## REFEREANCE

[1] J. P. Amaro, F. J. T. E. Ferreira, R. Cortesao, N. Vinagre and R. P. Bras, "Low cost wireless sensor network for in-field operation monitoring of induction motors," in *IEEE International Conference on Industrial Technology (ICIT)*, pp. 1044-1049, 2010

[2] S. Aeron, V. Saligrama and Manqi Zhao, "Information Theoretic Bounds for Compressed Sensing," in *IEEE Transactions on Information Theory*, vol. 56, pp. 5111-5130, 2010.

[3] Zhuang Xiaoyan, Wang Houjun and Dai Zhijian, "Wireless sensor networks based on compressed sensing," in *3rd IEEE International Conference on Computer Science and Information Technology (ICCSIT2010)*, pp. 90-92, 2010.

[4] A. Pepe and M. A. Rodriguez, "Collaboration in sensor network research: an in-depth longitudinal analysis of assortative mixing patterns," in *Scientometrics*, vol. 84, pp. 687-701, 2010.

[5] A. Mahalanobis and R. Muise, "Object Specific Image Reconstruction using a Compressive Sensing Architecture for Application in Surveillance Systems," in *IEEE Transactions on Aerospace and Electronic Systems*, vol. 45, pp. 1167-1180, 2009.

[6] C. H. Chang and J. Ji, "Compressed sensing MRI with multichannel data using multicore processors," in *Magn. Reson. Med.*, vol. 64, pp. 1135-1139, Oct, 2010.

[7] K. Choi, J. Wang, L. Zhu, T. S. Suh, S. Boyd and L. Xing, "Compressed sensing based cone-beam computed tomography reconstruction with a first-order method," in *Med. Phys.*, vol. 37, pp. 5113-5125, Sep, 2010.

[8] J.Luo,L. Xiang and C. Rosenberg, "Does compressed sensing improve the throughput of wireless sensor networks?" in *IEEE International Conference on Communications (ICC)*, pp. 1-6, 2010.

[9] E. Correia Pinheiro, O. A. Postolache and P. Silva Girao, "Implementation of compressed sensing in telecardiology sensor networks," in *Int. J. Telemed. Appl.*, vol. 2010, pp. 127639. Epub 2010 Sep 21, 2010.

[10] J. V. Capella, A. Bonastre, R. Ors and M. Peris, "A Wireless Sensor Network approach for distributed in-line chemical analysis of water," *Talanta*, vol. 80, pp. 1789-1798, Mar 15, 2010.

[11] Di Guo, Xiaobo Qu, Mingbo Xiao and Yan Yao, "Comparative analysis on transform and reconstruction of compressed sensing in sensor networks," in *WRI International Conference on Communications and Mobile Computing (CMC '09)*, pp. 441-445, 2009.

[12] J. Haupt, W. U. Bajwa, M. Rabbat and R. Nowak, "Compressed Sensing for Networked Data," in *IEEE Signal Processing Magazine*, vol. 25, pp. 92-101, 2008.

[13] Jia Meng, Husheng Li and Zhu Han, "Sparse event detection in wireless sensor networks using compressive sensing," in *43rd Annual Conference on Information Sciences and Systems (CISS 2009)*, pp. 181-185, 2009.

[14] J. N. Al-Karaki and A. E. Kamal, "Routing techniques in wireless sensor networks: a survey," in *Wireless Communications, IEEE*, vol. 11, pp. 6-28, 2004.

[15] J. Ko, T. Gao, R. Rothman and A. Terzis, "Wireless sensing systems in clinical environments: improving the efficiency of the patient monitoring process," in *IEEE Eng. Med. Biol. Mag.*, vol. 29, pp. 103-109, 2010.

[16] S. Ullah, H. Higgins, B. Braem, B. Latre, C. Blondia, I. Moerman, S. Saleem, Z. Rahman and K. S. Kwak, "A Comprehensive Survey of Wireless Body Area Networks : On PHY, MAC, and Network Layers Solutions," in *J. Med. Syst.*, Aug 19, 2010.

[17] M. P. Rajasekaran, S. Radhakrishnan and P. Subbaraj, "Elderly patient monitoring system uses a wireless sensor network," in *Telemed. J. E. Health.,* vol. 15, pp. 73-79, 2009.

[18] Chun Tung Chou, R. Rana and Wen Hu, "Energy efficient information collection in wireless sensor networks using adaptive compressive sensing," in *IEEE 34th Conference on Local Computer Networks (LCN 2009)*, pp. 443-450, 2009.

[19] H. J. Yoo, N. Cho and J. Yoo, "Low energy wearable body-sensor-network," in *Conf. Proc. IEEE Eng. Med. Biol. Soc.,* vol. 2009, pp. 3209-3212, 2009.

[20] Peng Zhang, Chen Chen and Minrun Liu, "The application of compressed sensing in wireless sensor network," in *International Conference on Wireless Communications & Signal Processing, (WCSP 2009)*, pp. 1-5, 2009.