Wireless Body Area Networks with Compressed sensing Theory

Mohammadreza Balouchestani,Member,IEEE

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

ABSTRACT

Wireless Body Area Networks (WBANs) consist of small intelligent wireless sensors attached on or implanted in the body. These wireless sensors are responsible for collecting, processing, and transmitting vital information such as: blood pressure, heart rate, respiration rate, electrocardiographic (ECG), electroencephalography (EEG) and oxygenation signals to provide continuous health monitoring with real-time feedback to the users and medical centers. In order to fully exploit the benefits of WBANs for important applications such as Electronic Health (EH), Mobile Health (MH), and Ambulatory Health Monitoring (AHM), the power consumption must be minimized. Since Wireless Nodes (WNs) in WBANs are usually driven by a battery, power consumption is the most important factor to determine the life of WBAN .The life expectancy of a WBAN for a given battery capacity can be enhanced by minimizing power consumption during the operation of the network. CS theory solves the aforementioned problem by reducing the sampling rate throughout the network. A combination of CS theory to WBANs is the optimal solution for achieving the networks with low-sampling rate and low-power consumption. Our simulation results show that sampling rate can be reduced to 25% without sacrificing performances by employing the CS theory to WBANs. This paper presents a novel sampling approach using compressive sensing methods to WBANs.

Index Terms- Wireless Body Area Network, Sampling-rate, Power consumption, Spares signal, Compressed sensing

1. INTRODUCTION

Wireless Body Area network (WBAN) as a subset of WSNs consists of small, intelligent wireless sensors placed in cloths, directly on the body or under skin, which are capable of establishing a wireless communication link. Figure 1 shows which the WBANs act as a subset of Wireless Sensor Networks (WSNs) [11].

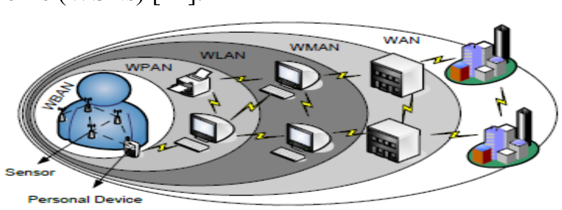

Fig.1. WBANs act as a subset of WSN [11]

By this convenient means, elderly people can keep track of their health conditions without frequent visit to their doctor's offices [2]. The low-power WBANs with CS theory can also be used to offer assistance to the disabled. The compressed sensing is a revolutionary idea proposed recently to achieve much lower sampling rate for sparse signal [8]. This theory says a small number of random linear measurements of compressible signals contain enough information for reconstruction and processing [7]. Generally, the biomedical signals are compressible and sparse and can be recovered by a small number of random measurements via ℓ_1 norm optimization [6]. They can be well reconstructed using minimize ℓ_1 norm, while satisfying the Restricted Isomerty Property (RIP) condition for the random measurements matrix $[\Phi]_{M\times N}$ (which offers by Compressed sensing theory) and orthogonal basis $[\Psi]_{N\times N}$. The challenges in WBANs are: limited power, low storage capacity, and limited processing capability. An important key to extend these networks to Electronic Health (EH), Mobile Health (MH), and Telemedicine is to minimize the power consumed of wireless nodes. Therefore, employing CS theory to WBANs seems to be an attractive solution for achieving autonomous networks with low-power, self-organizing and self-maintenance. Moreover, by employing the CS theory, WBANs will be used to offer more facilities to disable persons to measure important data of their body, either externally or internally. The structure of this paper is organized as follows: Section 2 offers a background about CS theory. Section 3 investigates sparse signals such as ECG and EMG signals in WBANs. Section 4 the simulation result on the sampling rate in ECG signals is shown. Finally, the conclusion is drawn in Section 5.

2. Overview of CS Theory

The CS theory is emerging as an attractive solution for WBANs as it provides compression, reducing the data size, and requiring fewer bandwidths to transmit data and therefore, requiring less power to process data. A basic block diagram of the CS scheme in transmitter and receiver sides is provided in Figure 2. In this chapter, we first discuss the CS theorem. Second, the reconstruction method to recover the original signal in the receiver side is investigated.

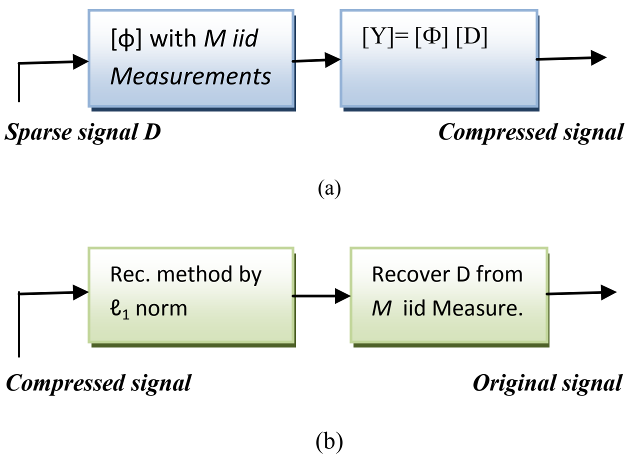

Figure 1: (a) CS in transmitter. (b) CS in receiver

2.1. Basic Theorem

Any compressible or sparse signal D in $\mathbb{R}^N$ can be expressed like [3]:

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

On the other hand, any compressible signal has a small number of large coefficients and a lot of number of small coefficients [1]. That is why; any compressible or sparse signal has K non-zero coefficients and $(N-K)$ zero coefficients with $K \ll N$. In the conventional sampling methods, we should start with large number of coefficients including zero and non-zero coefficients to determine location of non-zero coefficients. The CS theory offers a stable measurement metrics with M independent and identically distributed (i.i.d) measurements of the compressed signals such as $K \leq M \ll N$ [2]. Therefore the compressed signal $\mathbb{Y}$ is found as:

$$[\mathbb{Y}]_{M\times 1}=[\Phi]_{M\times N}[D]_{N\times 1} \quad (2)$$

By substituting (2) in (1) we have [12]:

$$[\Phi]_{M\times N}[\Psi]_{N\times N}[S]_{N\times 1}=[\Theta]_{M\times N}[S]_{N\times 1} \quad (3)$$

Thus CS scenario has two important steps. First step in CS offers a stable measurement matrix to ensure 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 [5]. Therefore, we can exactly reconstruct the original signal D with high probability via ℓ_1 norm with M iid Gaussian random measurements. The condition which guarantees the correctness of this recovery is given like:

$$M \geq cK \log (N/M) \quad (4)$$

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. Therefore, we can expect to recover *K-sparse* and original signal D with high probability from just M random Gaussian measurements [4].

3. Overview of WBANs

The WBANs as one of the applications of WSNs are used to design inexpensive and continuous health monitoring with real-time update of medical records via internet. The increasing use of wireless network and the constant miniaturization of electronic device has empowered the development of WBANs in electronic health monitoring that is now going to a step further by becoming Internet Health (IE). By this convenient means, people can keep track of their health condition without frequent visits to their doctors. The interaction with the user or other persons is usually handled by a Personal Digital Assistant (PDA) or smart phone, which acts as a sink wireless node for data of the WSNs [7]. The WBAN consists of two main parts: multiple Wireless Body Sensor Units (WBSUs) and a Wireless Body Center Unit (WBCU). The WBSUs perform vital medical data acquisition, data processing, data transmission and also provide some basic user feedback. The WBCU links multiple sensor units, performs data collection, data compression and event management. Then the physiological information will be transmitted wirelessly to the medical center [8]. If an emergency is detected, the physicians will immediately inform the patient by sending appropriate messages through WSNs. Regarding the propagation of electromagnetic (EM) waves in the human body, the wireless sensors provide signals to process and transmit through the network. In WBANs, the body acts as a communication channel and wireless sensors as transmitter or receiver. By comparing the amount of attenuation power with normal value the problem is detected. In order to determine the amount of power lost due to heat dissipation a standard measure of how much power is observed in tissue is used: the Specific Absorption Rate (SAR). The WBANs act as a subset of WSNs with its own features. A schematic comparison of WBANs and WSNs is given in Table 1. Due to the strong heterogeneity of the applications of WBANs in the practice, data rates will vary strongly, ranging from simple data at a few Kbps to video streams of several Mbps [9]. Table 2 provides some important features of medical applications such as data rate, bandwidth and accuracy.

Table 1.Campure of WBANs and WSNs

Parameter	Wireless Sensor Networks	Wireless body Area Networks
Scale	Monitored many environments (Meters/Kilometers)	Human body (Centimeters/ Meters)
Result-accuracy	Through wireless node redundancy	Through wireless node accuracy and robustness
Mode size	Small is preferred, but not important	Small is essential
Node lifetime	Several years/months	Several years/months
Power supply	Difficult to replaced	Impossible to replaced in some cases
Technology	WLAN, Zig Bee, Bluetooth	Low power technology required
Network topology	Very likely to be fixed or static	More variable due to body movement

Table2.Some important feathers of medical applications

Application	Data rate	Bandwidth	Accuracy
ECG	288-350 Kbps	100-1000 Hz	12 bits
EMG	320-990 Kbps	0-10000 Hz	16 bits
EEG	43.2-65 Kbps	0-150 Hz	12 bits
Blood saturation	18-34 bps	0-10 Hz	8 bits
Temperature	120-155 bps	0-8 Hz	8 bits
Glucose monitoring	1600-1950 bps	0-50 Hz	10 bits

3.1. Sparse signals in WBANs

Fortunately, some signals in WBANs such as Electrocardiography (ECG), Electroencephalography (EEG), and Electromyography (EMG) are sparse or near sparse and can be recovered by small number of measurements. According to this approach, the CS theory can be employed in WBANs to minimize sampling-rate and power consumption. These signals have K non-zero coefficients and (N-K) zero coefficients with $K \ll N$ and can be well recovered using M projects or measurements such as $K \leq M << N$. To investigate this issue, a set of ECG, EEG and EMG waveforms and data are adopted from MIT-BIH medical database [11]. The ECG signal is a qualitative analysis of the electrical potential which nodes generate during the cardiac cycle to simulate the myocardium and be acquired using three or four electrodes connected to body. The patient's Heart Rate (HR) and Heart Rate Variability (HRV) are usually monitored to handle the evolutions [12]. The EEG signals are recording of electrical activity of the brain. The EMG signals are used for evaluating and recording the electrical activity, which is produced by skeletal muscles. As the result, as long as, in these signal we have small number of non-zero coefficients, the CS theory can be applied to reduce load of sampling. Furthermore, the D data vector in WBANs is sparse vector, because the PDA needs to collect only M bits instead of N bits of data ($M \approx K$–*sparse*) through the network. In the WBANs with N wireless sensor, sensor i is acquiring a sample Di of the body. The final goal in WBANs for medical applications is to collect Data vector $D = [D_1, D_2 \ldots\ldots, D_N]$ of N wireless sensors. D has M-*Sparse* in a proper basis like:

$$\Psi = [\Psi_1, \Psi_2 \ldots \Psi_N] \quad (5)$$

CS suggests that, under certain condition, instead of collecting data vector D we can collect compressed vector $[Y] = [\Phi]\ [D]$, where Φ is $(K \times N)$ sensing Matrix whose entries are i.i.d random variables. In *non-CS* scenario a node is receiving N-1 packets and sends out N packets ((N-1) received packets plus its data) each packet corresponding to data sample from a node. In WBANNs with CS theory the PDA needs only to receive M ($M \approx K$-*sparse*) packets [10]. In order to use CS, each node needs to know the value of Compressed Ratio ($CR=N/K$) that is constant and value of N [16]. The node i computes $K=N/CR$ and generates K values Φ_{ji} ($1 \leq j \leq k$) and creates a vector $D_i\ [\Phi_{1\,i,}\ \Phi_{2\,i\ldots}\ \Phi_{k\,i}]$, where D_i is its own data. Typically, node i would 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 would send exactly *K-Packets* corresponding to the aggregated column vectors. Now the difference between CS and non-CS operation becomes clear [1]: CS operation requires each node to send exactly M packets irrespective of what it has received and each node needs to know CR and N and then computes value of ($M \approx K$). The received vector in PDA can be written as:

$$[Y]_{M \times 1} = [\Phi]_{M \times N}\, [D]_{N \times 1} \quad (6)$$

Consequently, the received vector in PDA is a condensed representation of the sparse events.

4. Simulation Results

Our simulation results show that the sampling-rate in ECG signals can be reduced to 25% without sacrificing performance of the ECG signals and with further decreasing the sampling-rate or power consumption, the performance is gradually reduced. The simulation results are produced using the simulator developed in C^{++} and MATLAB.

4.1. Simulation Results on Sampling Rate

As the behavior of the ECG, EEG, and EMG signals are approximately the same, we only investigate and simulate sampling-rate for ECG signals by applying the CS theory. In this simulation, we got the following assumptions.

►Total number of (coefficients) =1024.

►K as a number of non-zero coefficients

►M as a number of random linear measurements should be found from the following equitation:

$$\begin{cases} M \geq cK \log N/K \\ K \leq M \ll N \end{cases} \tag{7}$$

►c as a constant =1.5.

►Nyquist-rate=2048.

►Compressed Ratio (CR) =N/K.

Figure 4 shows the results for *K=100, K=200, K=300*. Consequently, the sampling-rates can reduce to 25% by applying the CS.

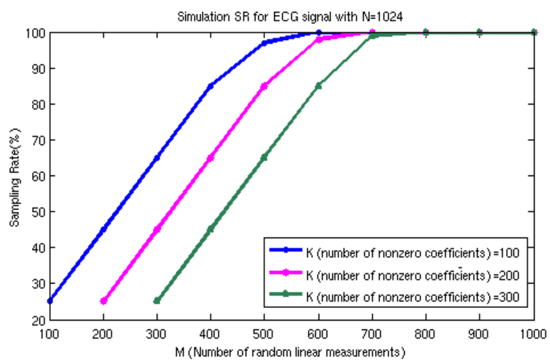

Fig.4 the simulation of SR for K=100, K=200, K=300

Our results show that by employing the CS the WBANs can achieve a higher transmission, a lower time delay and higher probability of success of data transmission.

5. Conclusion

WBANs are one area that have not yet experimented the benefit that CS theory might provide. In this paper, we have investigated the benefit of applying the CS theory to data collection in the WBANs. We first described how to employ the CS theory to WBANs for achieving low-sampling rate. Second, we formulated the requirements to apply the CS theory in WBANs. We also discussed on employing the CS theory to the WBANs to design low-power network in order to provide continuous health monitoring systems with real-time feedback to the users or medical centers. From the simulation results, we investigated that sampling-rate in ECG signals can reduce to 25%.

6. Further Works

We have investigated how to employ the CS theory in ECG signals. It will be part of our future work to develop the CS theory to other signals in the WBANs like: EEG, EMG, blood pressure. We will be looking at the combination of the CS theory to WBANs to provide low-power network in order to extend Electronic Health (EH) systems.

References

[1] M. Balouchestani, K. Raahemifar and S. Krishnan, "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, pp. 1-4, May,2011.

[2] Mohammadreza Balouchestani, Kaamran Raahemifar, Sridhar Krishnan ,"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,pp.122-125, , July, 2011.

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

[4] M. Doneva, P. Bornert, H. Eggers, C. Stehning, J. Senegas and A. Mertins, "Compressed sensing reconstruction for magnetic resonance parameter mapping," Magn. Reson. Med., vol. 64, pp. 1114-1120, Oct, 2010.

[5] D. L. Donoho, "Compressed sensing," Information Theory, IEEE Transactions on, vol. 52, pp. 1289-1306, 2006.

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

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

[8] Hang Su and Xi Zhang, "Battery-dynamics driven tdma mac protocols for wireless body-area monitoring networks in healthcare applications," Selected Areas in Communications, IEEE Journal on, vol. 27, pp. 424-434, 2009.

[9] M. A. Hanson, H. C. Powell, A. T. Barth, K. Ringgenberg, B. H. Calhoun, J. H. Aylor and J. Lach, "Body Area Sensor Networks: Challenges and Opportunities," Computer, vol. 42, pp. 58-65, 2009.

[10] Huasong Cao, V. Leung, C. Chow and H. Chan, "Enabling technologies for wireless body area networks: A survey and outlook," Communications Magazine, IEEE, vol. 47, pp. 84-93, 2009.

[11] M. Klemm and G. Troester, "Textile UWB Antennas for Wireless Body Area Networks," Antennas and Propagation, IEEE Transactions on, vol. 54, pp. 3192-3197, 2006.

[12] B. Latre, B. Braem, I. Moerman, C. Blondia, E. Reusens, W. Joseph and P. Demeester, "A low-delay protocol for multihop wireless body area networks," in Mobile and Ubiquitous Systems: Networking & Services, 2007. MobiQuitous 2007. Fourth Annual International Conference on, 2007, pp. 1-8.