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Wireless Body Area Networks Based on Compressed Sensing Theory

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Abstract

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Mohammadreza Balouchestani Asli

Ph.D., Electrical and Computer Engineering Department, Ryerson university, Toronto, Canada, 2013

In this research, the effective sampling method known as Compressed Sensing (CS) theory is applied to Wireless Body Area Networks (WBANs) to provide low power and low sampling-rate wireless healthcare systems and intelligent emergency care management systems. The fundamental contribution of this work can be divided into three areas. 1) We propose two new algorithms in the sensing, measurement, and processing area to compress biomedical data. 2) In the communication area, one new channel model based on CS theory is defined to transmit compressed data to the receiver side. 3) In the receiver side or reconstruction area, two new algorithms for recovering the original biomedical data are presented to recover the original data. Our results will be divided into three areas. 1) We employ the proposed algorithms to WBANs with a single biomedical signal (i.e. Electroencephalography [ECG] signals as a sample signal). In this area, the simulation results illustrate an increment of 10% improved for sensitivity in receiving compressed ECG signals. The simulation results also illustrate a 25% reduction of Percentage Root-mean-square Difference (PRD) for ECG signals on the receiver side. In addition, they confirm the ability of CS to maximize the prediction level for received the ECG signal at either Gate Ways (GWs) or Access Points (APs). 2) We illustrate that the proposed algorithms can be employed in WBANs with multiple biomedical signals to enhance current health care systems into low-power wireless healthcare systems. In this area, the simulation results confirm that for a particular WBAN, including *N* biomedical signals, the sampling-rate can be reduced by 25-35% and power consumption by 35-40%, without sacrificing the network's performance. 3) Here improvements for wireless channel feature between BWSs and either GWs or APs are shown. In this area, the results demonstrate that CS is able to maximize signal amplitude to 25-30% at the receiver as well as distance between transmitter and receiver BWS to 30%. Moreover, these results confirm that path loss can be reduced to 25%.

Acknowledgments

I started my studies in Sept. 2010. This wonderful journey was not possible without the help and support of many people. First and foremost, I would like to express my deep gratitude to my research supervisors, Dr. Kaamran Raahemifar and Dr. Sridhar Krishnan, for their enthusiastic encouragement, guidance, and valuable critiques of this research. Dr. Raahemifar was always available, whether it was for academic advice or just a friendly chat. His mentorship was paramount in providing me with research topics and guiding me on how to come up with the best solution for research obstacles. Dr. Krishnan provided comprehensive research support and encouraged me to foster new skills. They have helped me during one of the most important and sensitive parts of my life. I appreciate their vast knowledge and professional skills in many areas (i.e., vision and ethics), and their assistance in disseminating research results. Without their continuous professional advice and help, this research would not have been possible. For that, I am forever indebted to them. I wish to express my deep gratitude to all members of internal and external committees for their helpful guides.

I would also like to thank all of the generous people who have shared their time and resources with me. This includes (although not limited) to my friends, colleagues, and staff at the Department of Electrical and Computer Engineering at Ryerson University, especially my wonderful friends at the Signal Analysis (SAR) and Integrated Circuits and Smart Systems (ICSS) Laboratories. Their continuous support at every turn of the road towards completion of my studies is greatly appreciated.

Dedication

To my wonderful family for their unconditional love, enormous support and continuous encouragement.

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List of Abbreviations

CS	Compressed Sensing
WBAN	Wireless Body Area Networks
BWS	Biomedical Wireless Sensors
GW	Gate Way
AP	Access Point
PL	Path Loss
BSBL	Block Sparse Bayesian Learning
SMS	Sensing Matrix Selection
LCDP	Low Complexity Detection Procedure
CHM	Continuous Health Monitoring
SBST	Software Based Self Test
EH	Electronic Health
MH	Mobile Health
AHMS	Ambulatory Health Monitoring System
RIP	Restricted Isometry Property
ATM	Adaptive Threshold Mechanism
PFS	Peak Finding Scheme
SET	Shannon Energy Transformation
RSS	Row Selection Scheme
EMD	Empirical Mode Decomposition
MFC	Multipath Fading channel
SSI	Structural Similarity Index
PRD	Percentage Root-mean-square Difference
PPP	Positive Predication Percentage
SP	Sensitivity Percentage
ECG	Electrocardiography
EEG	Electroencephalography
EMG	Electromyography
DP	Detection Probability
IH	Internet Health
WSN	Wireless Sensor Network
MAP	Maximum A Posteriori
PDF	Probability Density Function
BAN	Body Area Network

Chapter 1

Introduction

1.1 Motivation

The main drawback of current healthcare systems is the use of wired/fixed systems and their associated wired biomedical sensors. They are also restricted by size, patient's mobility, power, and transmission capacity. Figure 1.1 shows major components of Ontario's health care spending during 2010 to 2011. From this figure we also see that Ontario's total health care budget in 2010–11 was $44.77 billion or 40.3 percent of everything the provincial government spends on programs [1]. Figure 1.2 shows Ontario population for 1971 to 2036.

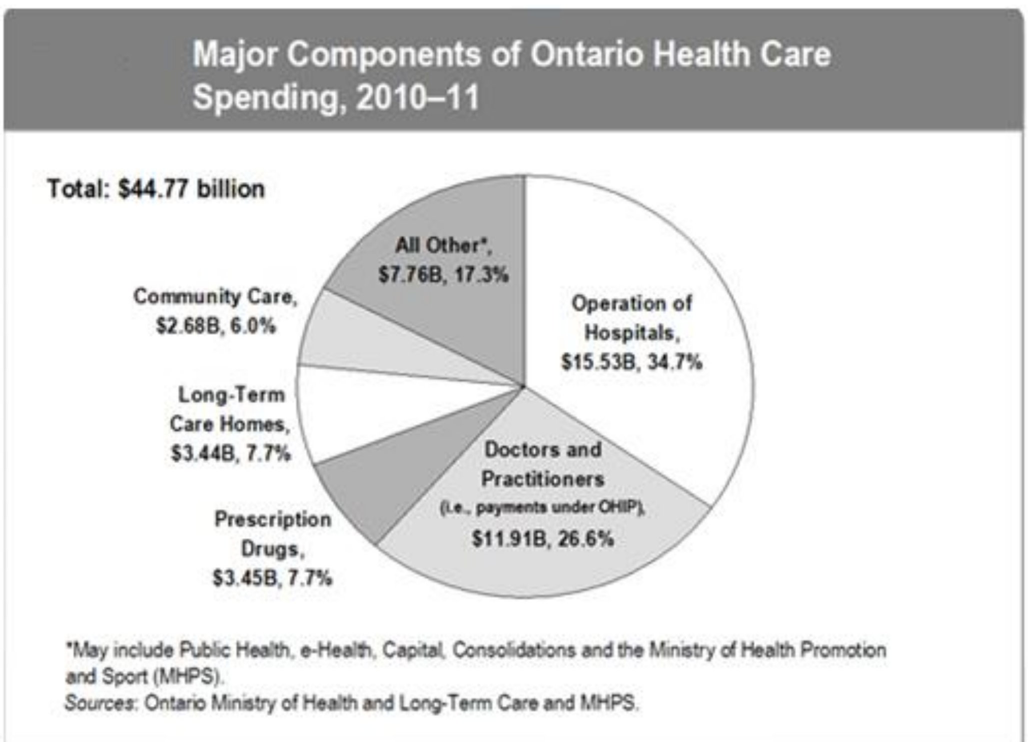


Fig.1.1: Health Expenditures for 2010-2011 in Ontario [1].

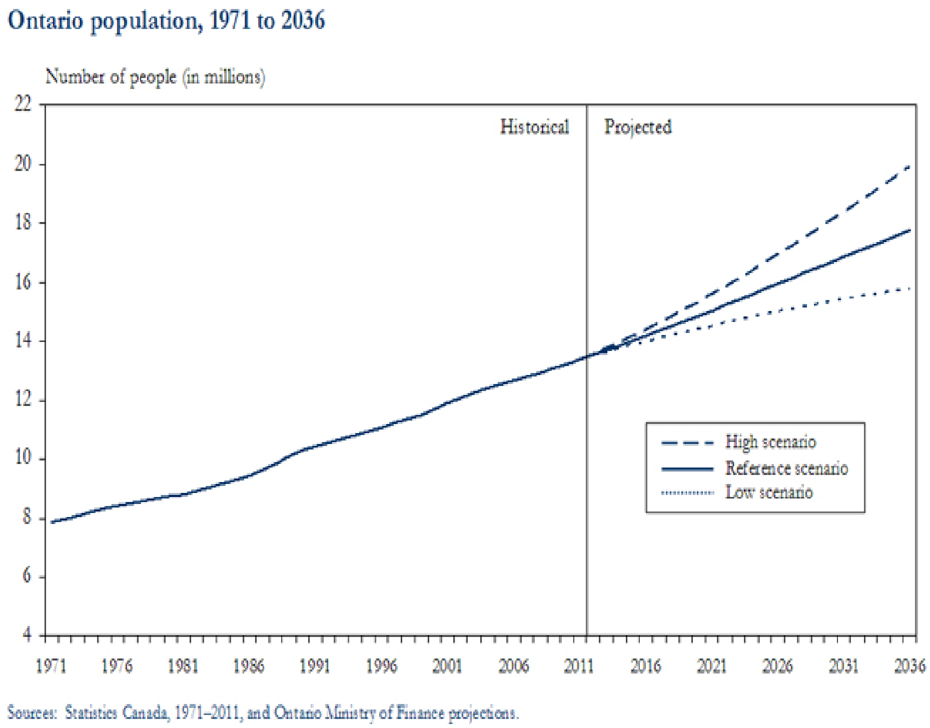


Fig. 1.2: Ontario population for 1971 to 2036 [2].

Figs. 1.2, show that Ontario's population and hospitalization costs have increased dramatically in recent years. Figure 1.3 emphasizes a significant rise in elderly people in Ontario in the near future who will be in need of specific healthcare.

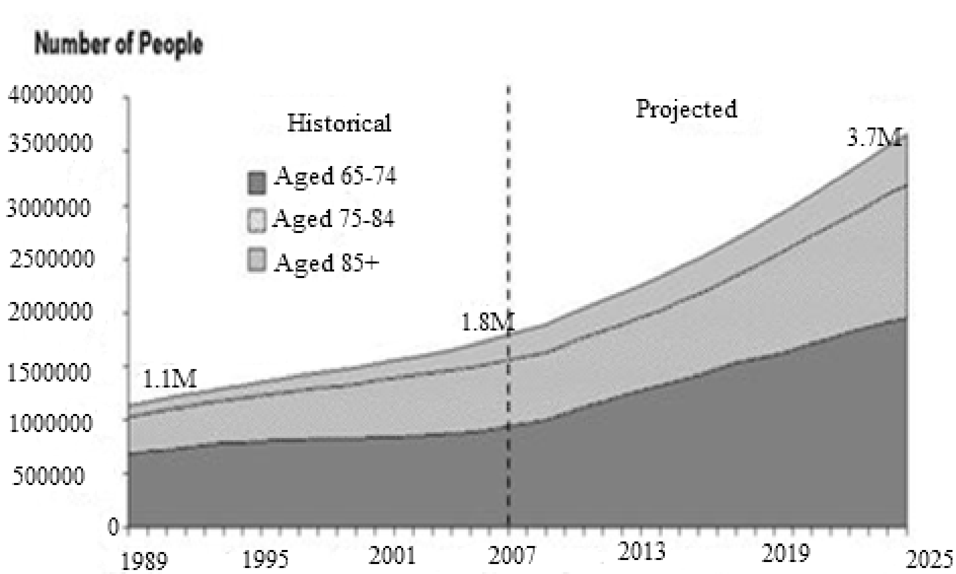


Fig.1.3: Ontario population for different ages [2]

To expand the current healthcare systems to Electronic Health (EH), Mobile Health (MH), Internet Health (IH), and Ambulatory Health Monitoring Systems (AHMSs), the power consumption and sampling rate should be kept a minimum value. Therefore, there is a critical need to minimize hospitalization time and costs for the next generation. This is our main motivation for providing new wireless healthcare systems. That is why the current healthcare systems need to be further enhanced in order to achieve extended mobility, improve signal integration and visualization, and provide further adaptations to medical experts through wireless monitoring of several patients at the same time. Since monitoring in the healthcare system continues over a rather long period of time, the quantity of data grows quickly. Therefore, it is important to reduce the load of sampling by merging the sampling and compression steps to reduce the storage usage, transmission times, and power consumption in order to provide Wireless Healthcare Systems (WHSs) [3, 4]. The WHSs provide vital information from a human body to physicians and doctors anytime and anywhere by removing constraints of time and location of patients, while increasing both the mobility and the quality of healthcare systems [5]. The fundamental motivation of this work is to establish new and low sampling algorithms based on CS theory in order to change current healthcare systems into low power wireless healthcare systems. Over the past few years, a new theory of CS has begun to emerge, in which the signal is sampled and simultaneously compressed. The basic idea of CS theory is that when the biomedical signal is sparse in terms of either a number of non-zero coefficients or a number of non-zero blocks, relatively few well-chosen observations suffice to reconstruct the original signal. Then, rather than measuring each sample and afterward computing a compressed representation, CS theory suggests that we can measure compressed representation directly.

The CS is a revolutionary idea proposed recently to achieve the much lower sampling rate for a sparse signal. CS theory states that many biomedical signals are sparse or, in practice, near sparse and can be compressed and recovered by a small number of random linear measurements [5]. In other words, the small number of random measurements contains sufficient information to process, transmit, and recover (fewer measurements instead of huge samples). The CS theory can reduce the number of bits of information; consequently, it increases the lifetime of wireless nodes by decreasing the power consumption. By applying the CS theory, the data size is reduced, fewer bandwidths are required to transmit data, and less power consumption is required to process data. Figure 1.4 shows our model for this motivation.

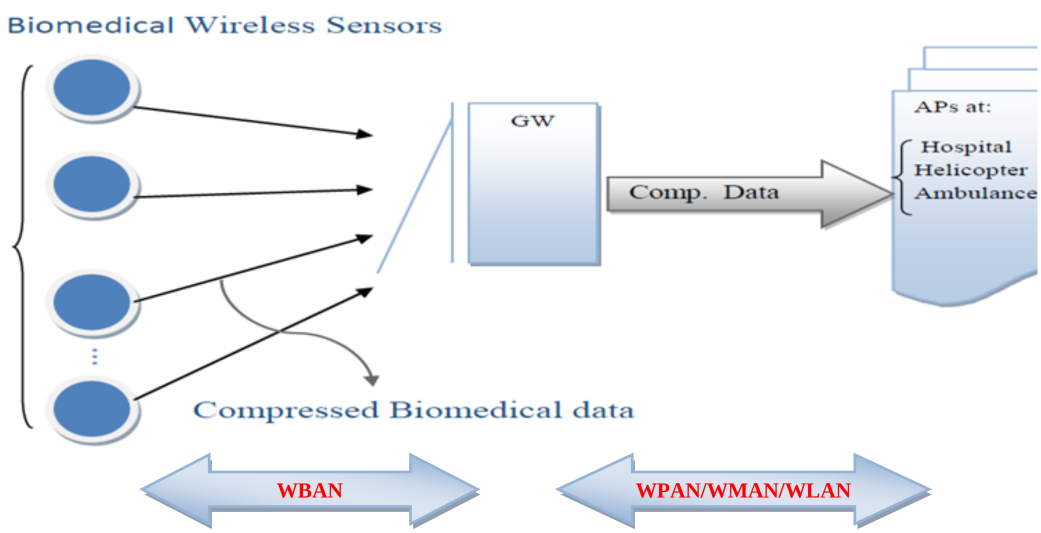


Fig.1.4:Compressed sensing in Wireless body area networks

As depicted in Fig.1.4, biological data are collected and compressed by BWSs, and the compresed data are then transmitted to APs via GWs in the hospital and medical centers for diagnostic and therapeutic purposes. Fig.1.4 also shows that compressed biomedical data can be transmitted to the hospitals and medical centers through particular types of wireless networks, such as Wireless Personal Area Networks (WPANs), Wireless Metrapolitan Area Networks (WMANs), or Wireless Local Area Networks (WLANs).

1.2. Wireless Healthcare Systems

The WHSs consist of small intelligent BWSs attached to or implanted into the body to provide continuous and real-time feedback to the users or medical centers in order to update health monitoring systems [6]. They are responsible to sense, collect, process, and transmit the vital signals of patients, such as blood pressure, brain activity, heart rate, ECG, Electroencephalography (EEG), and Electromyography (EMG). The WHSs are expected to provide breakthrough technology in healthcare areas such as EH, home care, telemedicine, and physical rehabilitation. To expand the applications of WHSs to EH, MH, Internet Health (IH), and Ambulatory Health Monitoring Systems (AHMS) the power consumption and sampling rate should be kept a minimum value.

The increasing use of wireless communication technology has empowered the development of wireless healthcare systems. Medical applications of WHSs include continuous waveform sampling of biomedical signals and monitoring of vital signals. They also perform vital medical data-acquisition, data processing, and data transmission. Advanced wireless healthcare systems will provide biomedical data to physicians and doctors anytime and anywhere by removing constraints of time and location of patients, while increasing both the mobility and the quality of healthcare systems.

1.3. Research Goals and Objectives

The fundamental objective of this research is to establish low sampling-rate algorithms based on CS theory and the collaboration of BSBL framework, SMS approach, LCDP procedure, new channel model for WBANs, and testing algorithm for WHSs in order to establish low-power Continuous Health Monitoring (CHM) with real-time feed-back. The research objectives are obtained by performing the following parts:

►Formulate and apply the CS approach for sparse and non-sparse biomedical signals.

►Establish a new algorithm based on CS theory and the collaboration with BSBL framework for recovering sparse and non-sparse biomedical signals.

►Employ SMS algorithm based on Dynamic Thresholding Approach (DTA) to find the best fit for random sensing matrix in CS theory.

►Propose an LCDP to capture compressed biomedical signals at the receiver side.

►Establish three new algorithms for WBANs based on CS approach and collaboration with BSBL, SMS, and LCDP.

►Establish new wireless channel model based on CS theory to improve features of wireless channels for transmitting the compressed biomedical signals to a main computer in hospitals or medical centers.

►Establish a new testing algorithm to increase the reliability and availability of the wireless medical networks.

Figure 1.5 shows our main block diagram for compressing biomedical signals on the transmitter side.

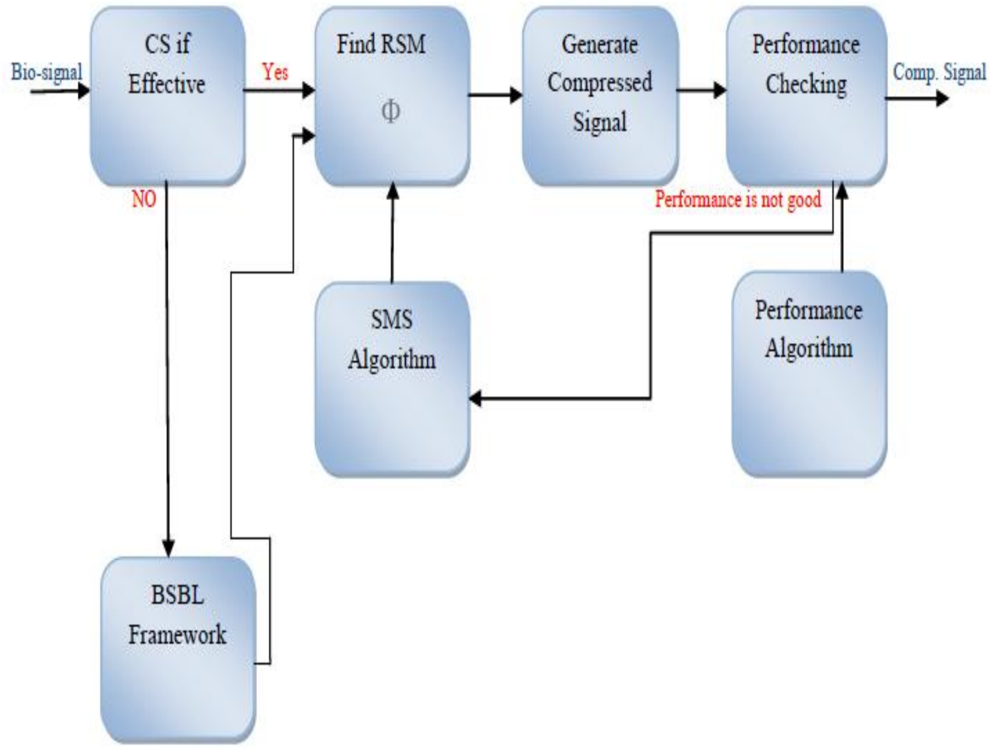


Fig.1.5: Compress biomedical signals/Transmitter

As depicted in Fig.1.5, the block diagram at the transmitter side of WBANs is composed of the following steps:

Step1: Select biomedical signal

Step2: Check the performance of CS

Step3: If CS is not effective, employ BSBL framework.

The main idea is that when the biomedical signal is sparse in terms of the number of non-zero coefficients or the number of non-zero blocks, relatively few well-chosen observations suffice to reconstruct the original signal. For sparsity in terms of the number of non-zero coefficients, CS is effective. Otherwise, for sparsity in terms of the number of non-zero blocks, the collaboration of CS theory and BSBL framework provides a robust algorithm for compressing as well as recovering the original biomedical signals.

Step4: Apply SMS algorithm for selecting random sensing matrix

Step5: Generate a compressed signal

Step6: Check the performance of compressed signal

Figure 1.6 shows our algorithms to recover the original signal on the receiver side.

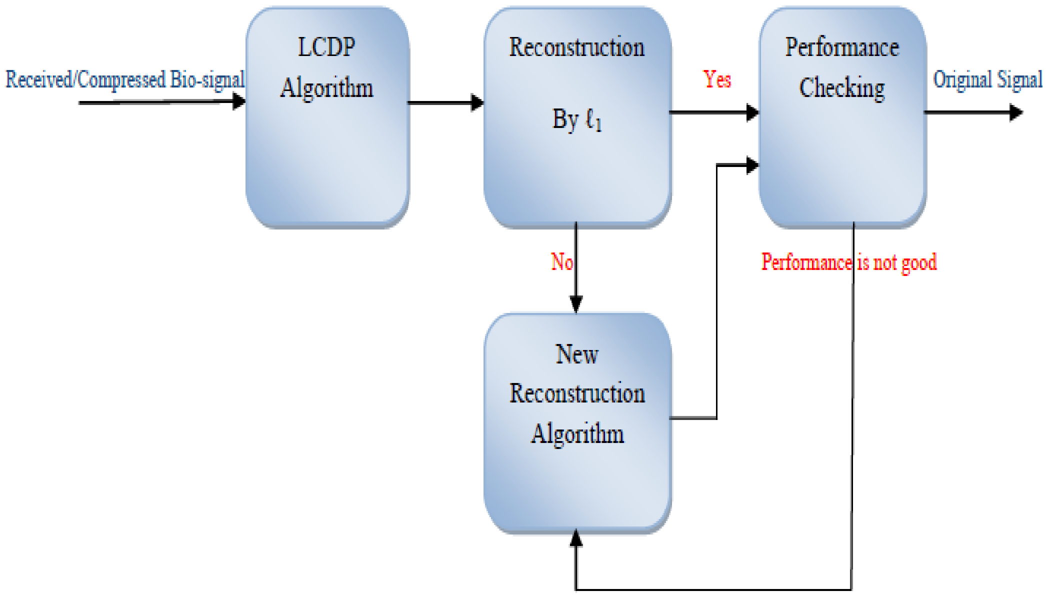


Fig.1.6: Recover original biomedical signal

The block diagram at the receiver side (either GWs or APs) consists of the following steps:

Step1: Receive compressed signal at GWs or APs

Step2: Apply LCDP algorithm for detecting the compressed signals with high probability

Step3: Employ reconstruction approach by ℓ_1

Step4: Apply the new reconstruction algorithm ,if needed.

Step5: Check the performance of the reconstruction algorithm

Step6: Provide the original biomedical signal in the hospitals or medical centers

Figure 1.7 illustrates our forecast for new healthcare systems for next generation based on CS theory. By employing the proposed algorithms in this work, the following outcomes are now possible:

►The biomedical signals are compressed by BWSs.

►The collected compressed biomedical data are then transmitted wirelessly to GWs or APs at hospital, ambulance, and helicopter.

►The GWs or APs can recover the original data from the compressed biomedical data for diagnostic and therapeutic purposes.

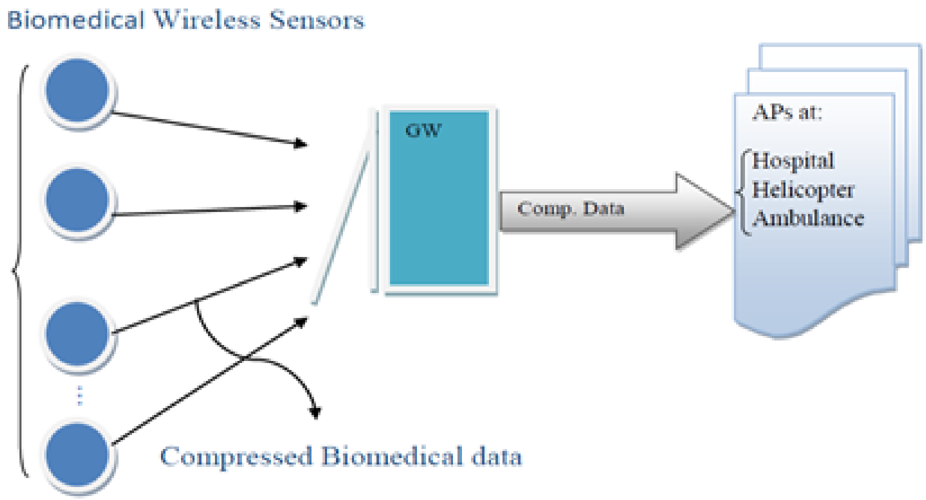


Fig.1.7: Forecast for new healthcare systems based on compressed sensing theory

1.4. Contribution and Methodology

The fundamental contribution and novelty of this work is to develop innovative algorithms to provide low-power and low sampling-rate new wireless and wearable healthcare systems. Thus, CS theory and the collaboration of BSBL, SMS, LCDP algorithms, new channel model, and new testing approach are used to provide new wireless and wearable healthcare systems. The research objective is obtained by employing the following contributions:

►*Collaboration of CS and BSBL*

In this aspect, our new algorithm based on CS theory and collaboration with the BSBL framework to establish advanced BSBL framework for sparse and non-sparse biomedical signals is presented. The main objective of the advanced BSBL framework is to recover non-sparse signals with or without a block structure. The main BSBL framework divides the non-sparse signal into non-overlapping blocks. By employing this framework a non-sparse signal can be partitioned into a concatenation of non-overlapping blocks, which only a few are non-zero. The main structure of this framework is to explore and exploit the intra-block-correlation in terms of the values of entries within each block. The advanced BSBL framework is also able to recover non-sparse signals that have no specific block structure because it has a pruning mechanism, which trims the blocks; therefore, it is effective for a signal with no clear block structure.

►*SMS Algorithm*

Two key features are needed for the successful implementation of CS approach: sparsity of the biomedical signal and a high degree of incoherence between the random sensing matrix and the sparsity basis. The fundamental purpose of this algorithm is to determine whether a random sensing matrix is a good candidate to ensure recovery of the original signal from the compressed signal. In this contribution our new algorithm is presented for finding the best fit for random sensing matrix for verifying two key conditions in the CS scenario is presented.

►*Reconstruction Algorithm*

The main purpose of this algorithm is to recover the compressed biomedical signals at GWs or APs with a good level of accuracy. This algorithm provides the theoretical guarantee that the original biomedical data can be recovered from the small number of random measurements or non-zero blocks in BSBL framework by solving a convex optimization problem. Moreover, this algorithm confirms that the information of the original signal is not damaged by the dimension reduction from a huge amount of coefficients to a small number of random measurements.

►*Detection algorithm*

In this contribution, we demonstrate a novel detection algorithm to capture compressed and received signals at GWs or APs. The proposed algorithm consists of two stages: 1. Feature extraction, which includes digital filtering and linear transformation 2. Decision making stage to locate the peak value in the biomedical signals.

► *Channel Model*

In this contribution, a new channel model for WBANs based on CS theory for transferring the compressed biomedical signals from the human body to main computer at the receiver side is presented. The main reason for this algorithm is to minimize the Path Loss (PL) and maximize received signal amplitude at the receiver.

►*Testing algorithm*

In this contribution, a new algorithm for testing BWSs also based on CS theory is demonstrated. The main purpose of this algorithm is to increase the reliability and availability of BWSs in the WBANs.

1.5. Thesis organization

The structure of this thesis is divided into main areas. In the first area, surveys of WSNs, WBANs, and CS theory are presented. In this area, we present the basic idea of CS theory, that is, when the biomedical signal is sparse in terms of the number of non-zero coefficients or the number of non-zero blocks, relatively few well-chosen observations suffice to reconstruct the original signal from the compressed signal. In the second area, WBANs with single and multiple biomedical signals are investigated. In next area, we confirm that a combination of CS and our proposed algorithms is the optimal solution for providing low power and low sampling-rate networks. Finally, wireless channels based on CS theory are illustrated for transmitting the compressed biomedical signals from the human body to either GWs or APs. Figure 1.8 shows pictorial structure of the thesis organization. The fundamental flowchart of this work is shown in Figure 1.9.

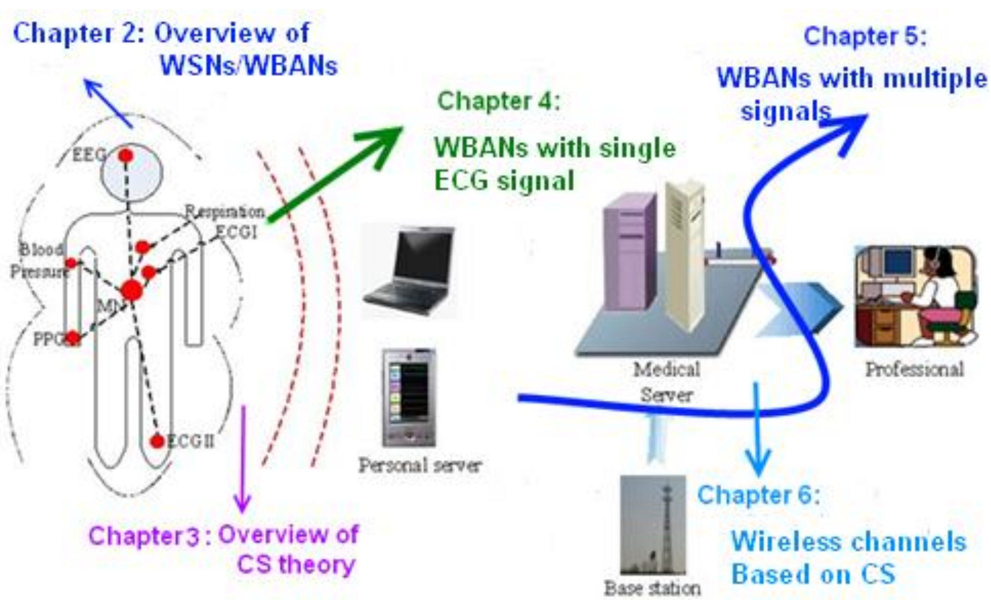


Fig. 1.8: Pictorial structure of thesis organization

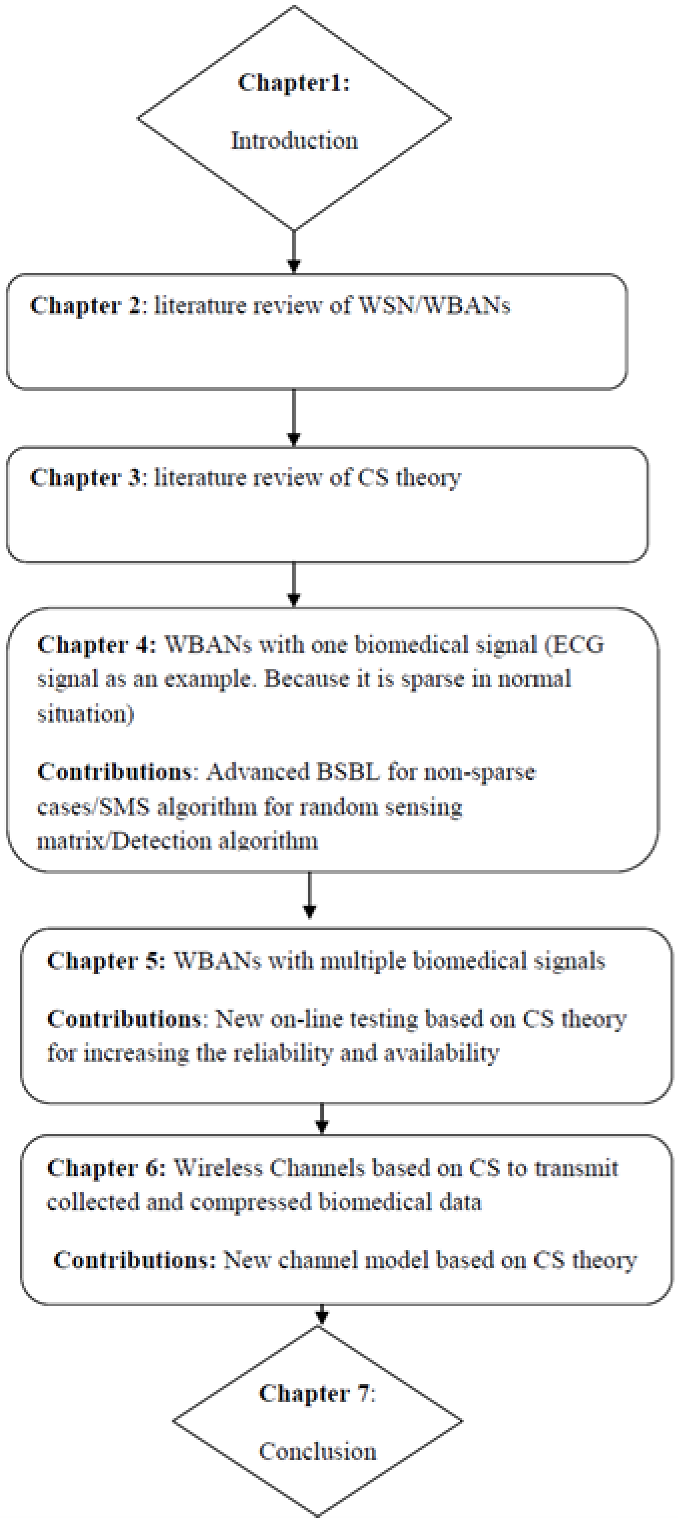


Fig.1.9: Structure of the thesis

As depicted in Fig.1.8, the thesis is organized into seven chapters. *Chapter* 2 illustrates an overview of WBANs as well as WSNs and applications of wireless healthcare systems. *Chapter* 3 provides a brief background of CS theory and reconstruction method. Theoretical background for this theory also is presented in this chapter. *Chapte*r 4 demonstrates the CS for WBANs with single ECG signals. The proposed algorithms are also examined for ECG signals in this chapter. The rest of this thesis is unfolded as follows: *Chapter* 5 applies CS theory to WBANs with more than one biomedical signal, and in *Chapter* 6 our new channel model based on CS theory is presented for transmitting the compressed biomedical signals from a human body to the GWs and then to APs in the hospitals and medical centers. Finally, main conclusions are presented in *Chapter* 7.

1.6. Plan for Next Chapter

In the next chapter, the overviews of WSNs and WBANs are presented, and then the constraints in the current network using conventional sampling methods are introduced. We show that wireless networks consist of a number of wireless nodes each with sensing, processing, communication, and power supply units to monitor and control the real-world environment's information. Further, we present that wireless networks are responsible to sense, collect, process, and transmit information such as pressure, temperature, position, flow, vibration, force, humidity, pollutants, and bioelectronics signals from the human body. The next chapter also discusses the problem of efficiently transmitting or sharing from and among a vast number of wireless nodes due to the energy and computation consumption of wireless nodes. The other problems include limited processing capability, low storage capacity, limited energy, and high sampling rate. The next chapter also emphasizes that the ideal wireless networks should be networked to consume very limited power, be capable of fast data acquisition, be reliable and accurate over the long term, cost little to purchase and install, and require no real maintenance. Figure 1.9 shows the plan for the next chapter. As depicted in Fig. 1.10, the following concepts are demonstrated in the next chapter:

►Introduce WSNs and important units.

►Present applications of WSNs.

►Define problems in WSNs.

►Present WBANs in general.

►Introduce medical applications of WBANs.

►Investigate problems in current WBANs.

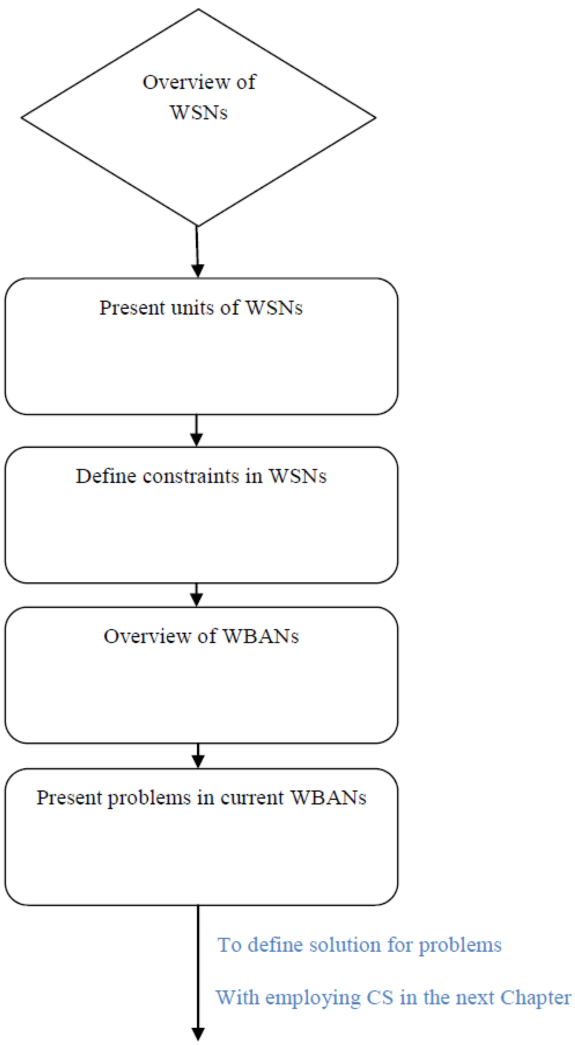


Fig.1.10: Plan for next Chapter

Chapter 2

Literature Review of WSNs and WBANs

2.1. Motivation

The current healthcare monitoring systems are large and use an inordinate amount of power; because they have limited transmission capacity, a patient cannot easily leave a healthcare facility and continue to be monitored. The main drawback of current systems is the location-specific nature of the system due to the use of fixed/wired systems. The need to increase patient mobility outside of medical facilities is currently limited because many biomedical sensors for medical monitoring do not have yet wireless capability. However, since BWSs are usually driven by a battery, power consumption is the most important factor determining the life of BWSs. The life expectancy of a BWS for a given battery capacity can be enhanced by minimizing power consumption during the operation of the network. Therefore, they need to be further enhanced in order to achieve extended mobility, improve signal integration and visualization, provide further adaptations to medical experts and wireless monitoring of several patients at the same time. Thus, the fundamental motivation of this chapter is to present a literature review of WSNs and WBANs as a subset of WSNs and important constraints to extend them to wireless medical systems. Figure 2.1 shows our plan in this chapter.

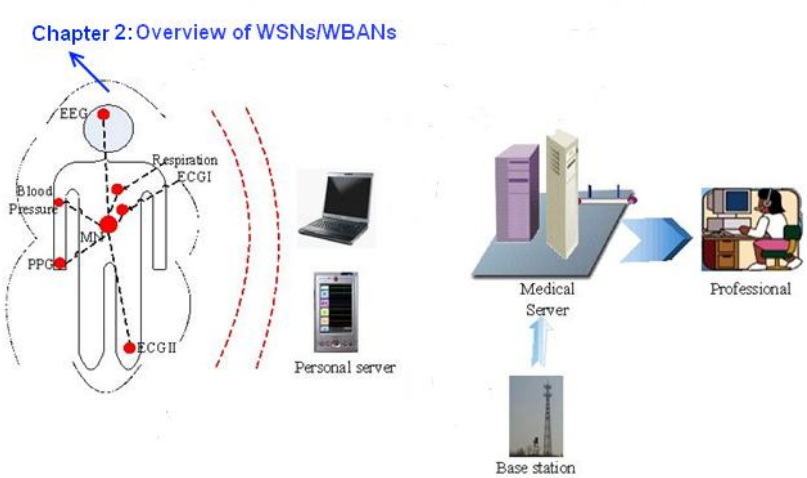


Fig.2.1: Plan for this Chapter

2.2. Overview of WSNs

WSNs consist of a large number of wireless nodes that are responsible for sensing, processing and monitoring environmental data. The wireless sensors collect information such as temperature, pressure, position, flow, humidity, vibration, biomedical data, force and motion to monitor the real-world [7, 8]. Wireless nodes can be deployed for monitoring scenarios such as industrial automation, traffic controlling, electronic wars, transportation automation, EH, and web controlling [9]. There are limiting parameters on a wireless sensor network, such as power consumption, lifetime, delay, size, bandwidth, signal distortion and cost. Wireless nodes have very low limited energy capacity and therefore, energy consumption is the most important factor to determine the lifetime in wireless sensor networks. A general structure provides a flexible and versatile platform to address the needs of a wide variety of applications. Basically, WSNs consist of a large number of Wireless Nodes (WNs) each with sensing, processing, communication, and power supply units to monitor information in the real-world environment. The WSNs are now used in a variety of fields such as health monitoring in designing EH, transportation automation in designing Traffic Control System (TCS), industrial process monitoring in designing Web Controlling System (ISC), and business and residential areas in designing Energy Management System (EMS). The problem of efficiently transmitting or sharing from and among a vast number of wireless nodes is a great challenge to the energy and computation consumption of wireless nodes. The ideal WSNs should be networked in order to be capable of the following; fast data distribution, reliability and accuracy over the long term, low cost to purchase and install, and no need for real maintenance. The WSNs are gaining market acceptance in numerous environments because they are both cheaper and faster to deploy than traditional wired-buses [10]. The WSNs are also widely used in a variety of applications to monitor the physical world via a spatially distributed network of small wireless sensors that have the ability to self-organize into a well-connected network. The network data transmission is accomplished through multi-hop routing from individual wireless sensors to the wireless sensors in the sink layer [11]. Figure 2.2 shows a block diagram of WSNs. They have the potential to allow sensing, processing, and monitoring in applications where it would have been previously impossible or too expensive, such as wireless health monitoring.

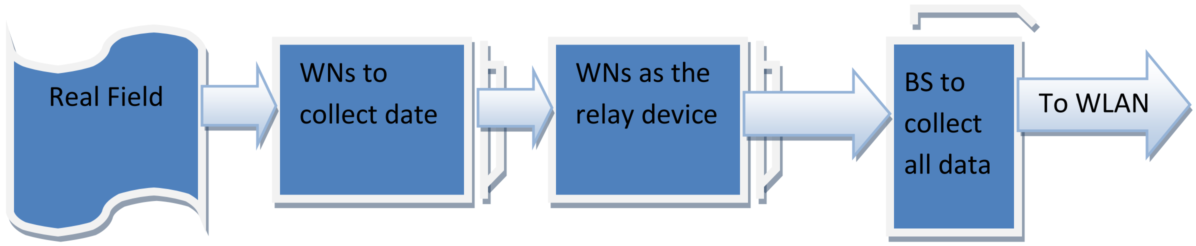


Fig.2.2: Basic block diagram for wireless sensor networks

In WSNs as a communication system, sources are wireless sensors, which collect some data of real-world environments; the channel, which l is the space between the wireless sensors, and the receiver which is another wireless sensor or BS [12, 13]. Each wireless node has four important units, namely, sensing, processing, communication, and power supply units. A basic block diagram of a wireless node is provided in Figure 2.3.

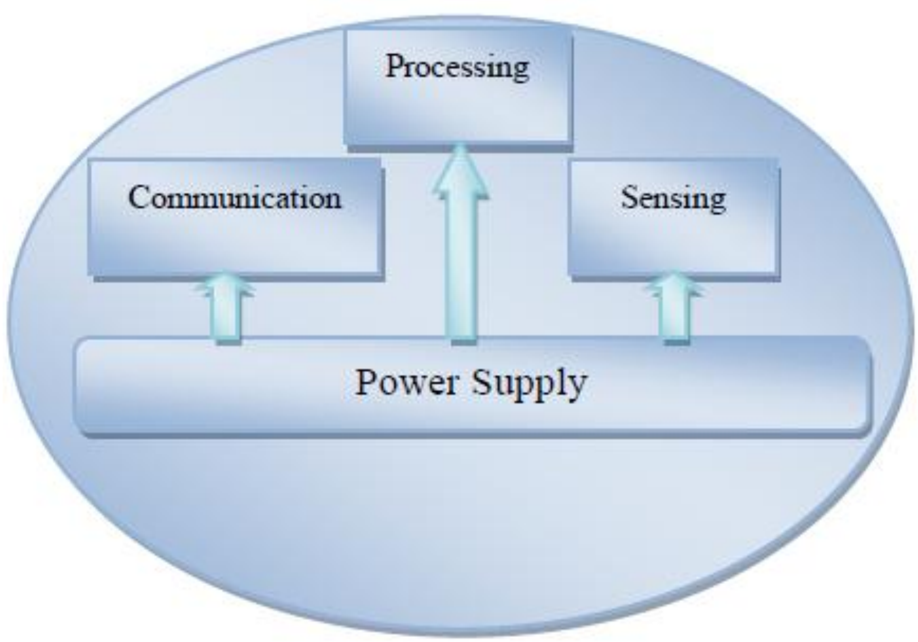


Fig.2.3: Block diagram of wireless nodes

Regarding the description above, the WSNs consist of wireless nodes, a combination of sensor technology, and a tiny battery with a wireless communication interface. Deployed within the area of interest, the devices organize into networks and allow for monitoring of process, environmental conditions, and events. The individual WNs must be capable of operating the planned hardware on a 100% duty cycle, 24 hours a day and for years. The problem of efficiently transmitting or sharing from and among a vast number of WNs makes great challenges for the WSNs [14]. In practice WSNs periodic data collection is required with a low data collection delay. The ideal WSNs should be responsible to collect, process, monitor and transmit data with low delay, low power, and high detection probability [15]. Figure 2.4 shows the structure of WSNs [16].

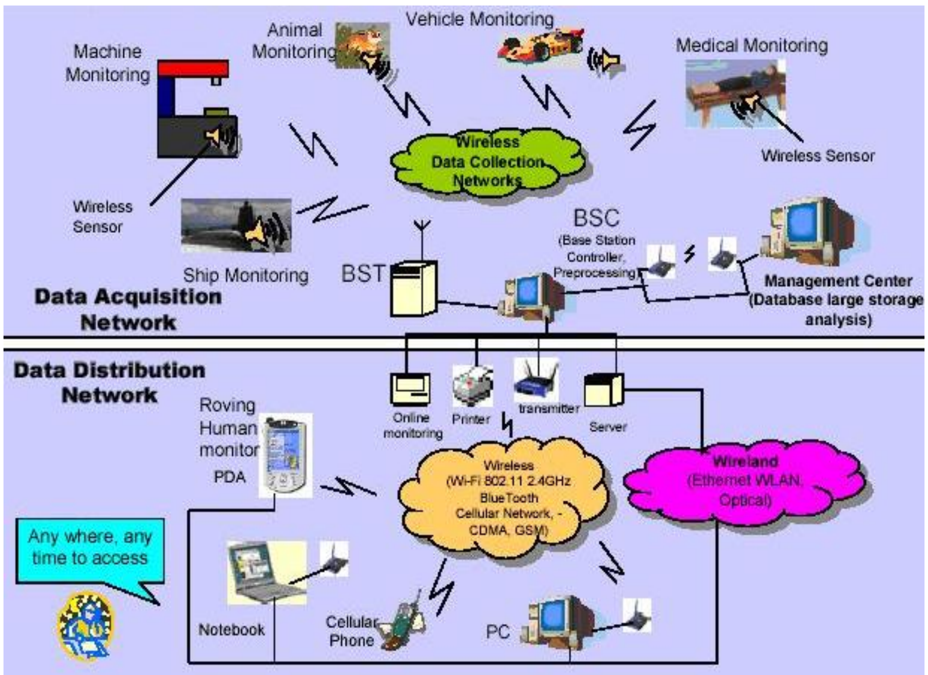


Fig.2.4: Structure of WSNs [16].

As a result, WSNs enable a significant value for a number of additional usages such as:

- Environmental control for power savings in heating, cooling, and lighting.
- Wireless health monitoring to provide continuous health monitoring systems.
- Device monitoring to prevent accidents and failures, or limit their consequences.
- Outdoor monitoring to track telluric activity or pollution in the atmosphere.
- Logging for traceability and causal analysis.
- Ambulatory health monitoring to promote healthy lifestyle.

Figure 2.5 shows some of the applications for WSNs.

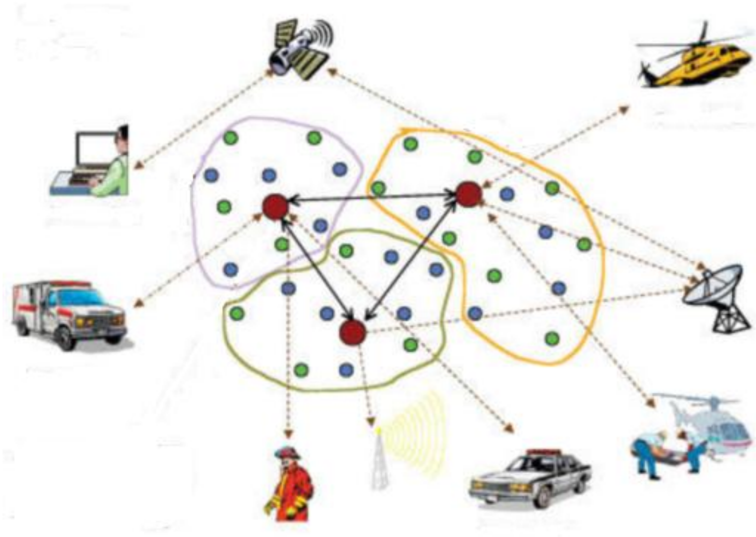


Fig.2.5: Applications of wireless sensor networks

2.2.2. Units of wireless nodes

This section presents an overview of units in each wireless node. The power of WSNs lies in the ability to deploy a large number of tiny wireless nodes that assemble and configure themselves. Each WN consists of important units such as Sensing Unit (SU), Power Supply Unit (PU), Wireless Communication Unit (WCU) and Controlling Unit (CU) [17, 18]. The important concept of WNs is based on a simple equation like:

$$\text{Power+ Sensing+ Processing+ Communication = Thousands of applications.} \quad (2.1)$$

Depending on the actual needs of the applications, the size of a wireless node may vary from the size of a shoe box (e.g. a weather station) to a microscopically small particle (e.g. military application or medical applications, where wireless nodes should be almost invisible or medical applications). Wireless nodes are standard measurement tools equipped with transmitters to convert signals from process control instruments into a radio transmission. Figure 2.6 shows units of WNs. Power consumption is the most important factor to increase the lifetime of WNs, because WNs are usually driven by battery and have very low energy. In most applications of WSNs recharging and replacing the power supply is impossible. The lifetime of the power supply can be increased by reducing the current drastically. Thus, each WN can be designed to manage its local power supply so that it can maximize its lifetime.

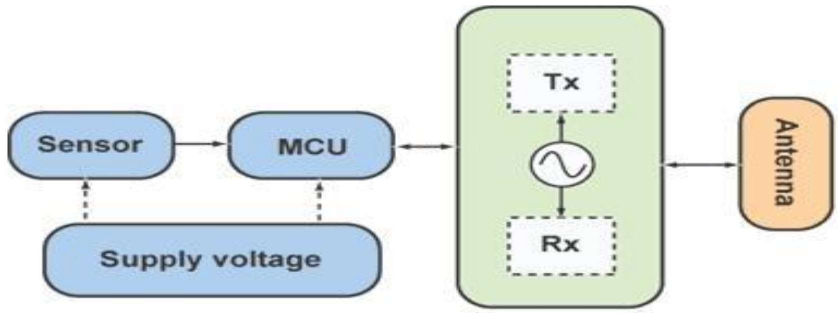


Fig.2.6: Units of wireless nodes [133]

The various communication modalities can be used in different ways to construct an actual communication network. Two common forms are so-called infrastructure-networks, and *ad-hoc* networks. In infrastructure-networks, wireless nodes can directly communicate with the Base Station (BS). If there are multiple BSs, these have to be able to communicate with each other. The number of BSs depends on the communication range and the area covered by the sensor nodes. In *ad-hoc* networks, wireless nodes can directly communicate with each other without an infrastructure. WNs may act as routers that forward messages over multiple hops on behalf of other nodes. In both methods, thousands of WNs should send their data to the BS, and thousands of bits are passed through the whole network that produces global traffic. The constraint is that sensors deployed are unattended and in large numbers, so it would be difficult to change or recharge batteries in the sensors. Therefore, all systems, processes, and communication protocols for wireless sensors must minimize power consumption. A functional block diagram of a wireless node is provided in Figure 2.7.

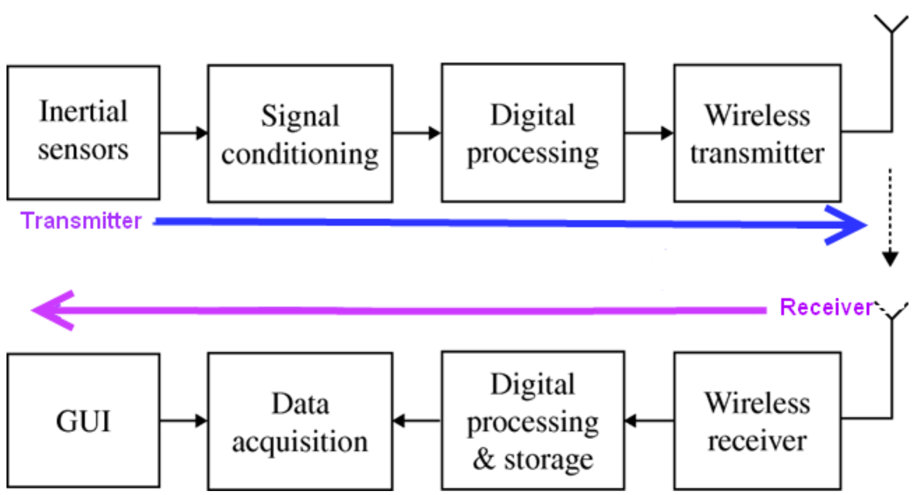


Fig.2.7: Block diagram of a wireless node

This block diagram provides a flexible and versatile platform to address the needs of a wide variety of applications. Therefore, depending on the WNs to be deployed, the signal conditioning block can be re-programmed or replaced. The communication unit can be swapped out as required for given application wireless range requirements and the need for bidirectional communication. The using of flash memory in WN allows the remote WNs to acquire data on command from a BS or to be sensed by one or more inputs to the WNs. Moreover, the embedded firmware can be upgraded through the WSN in the field. The microcontroller has a number of functions, including:

► Managing data collection from the WNs and BS.

► Performing power consumption management functions.

► Manipulating time modes in sleep, active and test modes.

► Managing the network protocols between the communication unit and sensing unit.

2.2.2.1. Power Supply unit

The PS unit is one of the important components in the WNs, and in most cases is a battery. Power is a primary constraint in the wireless sensor networks, and the power supply should provide energy for sensing devices, transmitter, receiver and microprocessors or microcontrollers. This fundamental power constraint further limits everything from data sensing rates and bandwidth, to node size, cost, security and weight. In addition, there is a focus on increasing the lifetimes of sensor nodes through power generation, power conservation, and power management. Today, power management technologies in WSNs are constantly evolving due to extensive research. The primary limiting factor for the lifetime of a WN is the energy supply. Each WN must be designed to manage its local supply of energy in order to maximize the total network lifetime. A WN has some important modes, such as sleep and active modes. To minimize power consumption it is important that a WN sends data only when required. By reducing the sampling rate in WNs the sleep time for WNs is increased and consequently, the power consumption is reduced. A WN periodically wakes up to acquire and transmit data by powering up; and then it goes back off-line to conserve energy thus, it must efficiently transmit a signal and allow the system to go back to sleep with minimal power use [153]. If WN decides to go in to sleep mode with t_1, the power reduces to P_{sleep} with t_{down}. WN comes back to active mode with τ_{up}. The energy in sleep mode is as follows [19]:

$$E_{sleep} = t_{down} / 2 + (t_1 - t_{down}) P_{sleep} \tag{2.2}$$

The energy in active mode can be expressed [19]:

$$E_{active} = (\tau_{up} - t_1) P_{active} \tag{2.3}$$

Therefore the energy saving is:

$$E_{saved} = E_{active} - E_{sleep} \tag{2.4}$$

As a result, in the WNs, switching to sleep mode is beneficial if $E_{overhead} \leq E_{saved}$ that $E_{onerhead}$ is as:

$$E_{overgead} = \tau_{up} / 2 \tag{2.5}$$

In a WN the transmission power is given by [21]:

$$P_T = R^2 / N \tag{2.6}$$

where R is the distance between source node and destination. The transmission rate in WN is controlled by several factors, including transmission power, sensitivity of the receiver, the gain and efficiency of the antenna, and the channel encoding mechanism. The transmission rate can be represented as follows [21]:

$$T_r = \sqrt{\log N / \pi N} \tag{2.7}$$

As a result, if the amount of information is decreased, the transmission power and the transmission rate are increased, and hence power dissipation is decreased. This result will be achieved by minimizing the sampling-rate in the WNs. The battery lifetime is related to the discharge rate or amount of current drawn. By applying a low sampling-rate procedure, the number of bits of information decrease and the current drawn into the power supply is dropped. In order to make a power supply with a long lifetime, we should reduce the power consumption by the units of each node. This is all due to the fact that maintenance and replacement of the power supply are expensive and difficult. Table 2.1 compares the power consumed in sleep and active modes for wireless nodes at different distances [22].

Table 2.1: Power consumption in sleep and active modes for wireless nodes at different distances

Maximum distance of WN	**Power consumed in active**	**Power consumed in sleep**

(m)	mode(mw)	mode(mw)
15	0.254004	0.003100
20	1.357128	0.004128
30	1.896128	0.005001
50	2.448749	0.005834
100	2.990791	0.005923
200	3.161297	0.006001
500	3.638891	0.062002
1000	3.897832	0.067001

2.2.2.2. Sensing Unit

The WNs are standard measurement tools equipped with transmitters to convert signals from process control instruments into a radio transmission. Varying size and cost, constraints directly result in corresponding varying limits on the energy available (i.e. size, cost and energy density of battery). The IEEE 1451 provides a standard for WNs to make it easier for different manufacturers to develop sensors and interfaces for wireless sensor networks. IEEE 802.11 is designed for WLAN and provides data transfer between computers and other devices, such as switches and routers. In IEEE 802.11 the data transfer rates are between 1 Mbps and 50 Mbps. The IEEE802.15.4 is designed for multiple data rates and multiple transmission frequencies. It is very flexible for WNs and is also useful for low power networks. The transmission frequencies in IEEE802.15.4 are 868 MHz, 902, 928 MHz, 2.48, 2.5 GHz and data rates are 20, 40 and 250 Kbps [23]. This standard supports star and peer-to-peer wireless networks and specifies the option to encrypt transmitted data. It is useful for a multi-hop mesh wireless network. As a result, the IEEE802.15.4 will become accepted in a large-scale wireless sensor network that has compressed data in wireless nodes according to compressed sensing theory. The IEEE802.15.4 protocol defines the physical and medium access control layers in the networking model, providing communication in the 868 to 915 MHz and 2.4 GHz bands and data rates up to 250 kb/s. The Zigbee protocol is designed on top of the IEEE 802.15.4's physical layers to support security and reliability with other devices. ZigBee builds a standard link communication layer for wireless sensor networks with high-security. ZigBee is focused on the star topology network with low-power wireless devices. Table 2.2 shows which physical principles may be used to measure various quantities.

Table2.2: Wireless sensors and their transducers

Application	Wireless sensor	Transducer
Physical Properties	Pressure	Piezoresistive, Capacitive
	Temperature	Thermistor, Thermo-mechanical, Thermocouple,
	Humidity	Resistive, Capacitive, Thermo-mechanical,
	Flow	Pressure, Thermistor
Motion Properties	Position	E-mag, GPS, Contact
	Velocity	Doppler, hall effect, Optoelectronic
	Angular velocity	Optical encoder
	Acceleration	Piezoresistive, Piezoelectric, Optical fiber
Contact Properties	Strain	Piezoresistive
	Force	Piezoelectric, Piezoresistive
	Torque	Piezoresistive, Optoelectronic
	Slip	Dual torque
	Vibration	Piezoresistive, Piezoelectric, Optical fiber, Sound,
Presence	Tactile/Contact	Contact switch, Capacitive, Piezoelectric, Optical fiber
	Proximity	Hall effect, Capacitive, Magnetic, Seismic, Acoustic, RF
	Distance/range	E-mag (sonar. Radar, lidar), magnetic, tunneling
	Motion	E-mage, IR, Acoustic, Seismic , Piezoelectric, Optical fiber, Sound, Ultrasound

2.2.2.3. Processing Unit

The Processing unit consists of microcontrollers or microprocessors, memory, interfaces, counters and timers. Regarding the application of the WSNs, the processing unit has many types of microcontrollers or microprocessors. Table 2.3 shows characteristics of microcontrollers in the WNs such as Bits, RAM, Flash, timers and power modes for active, idle, and sleep modes [23].

Table2.3: Characteristics of microcontrollers in wireless nodes

Feature	PIC16 F8X	MSP430 F14	SARM S1100	AT91 M428	MCH C05	RDC8 051	EM660 3	MX9328
Bits	8	16	32	64	8	8	4	16
Flash	68	60	60	128	128	64	64	64
RAM(B)	1	2048	2048	8	192	1024	964	128
Timers	1	3	3	6	1	1	1	2
Operating Voltage	2-6	1.8-3.6	3-3.6	2.7-3.6	3.3-5	2.7-5.5	1.2-3.6	1.6-3.3
Power Active(mw)	2	0.4	0.23	2	4.4	0.23	0.15	0.16
Power Idle Mode(mw)	1.65	1.3	2.5	1.8	1.95	1.1	0.85	0.74
Power Sleep Mode(mw)	0.012	0.014	0.032	0.028	0.01	0.01	0.01	0.0135
ADC(bit)	10	12	12	10	8	8	10	13

Based on table results, the microcontrollers such as EM 6603 and 8-bit microcontrollers such as AT90LS8538 have very limited computational ability and are used in small scale WSNs. The microcontrollers such as MC9338MXI and MSP430F149 have a tiny processing unit (TPU), and they are supported by the wide range of development tools to be able to perform various real-time control tasks. They are used in medium scale WSNs. The 32-64 bits microcontrollers such as ARMSA110, AT91M42800A are the best option for large-scale WSNs that usually consist of numerous nodes and sensors. They are based on the ARM architecture and offer a 16 KB cache, serial I/O and JJAG interface that are all designed on a single chip. They have storage of 1 MB SRAM and 4 MB of bootable flash memory. They also provide a connection with the sensors by the SPI interfaces and a 32-bit fast access register for urgent security. As well, they have three states or modes: sleep, idle, and active modes. Changing between states to reduce power is one of the important points for them. Remaining in sleep mode for more time by employing a low sampling-rate procedure is the best way to reduce power consumption. The power consumption in microcontrollers is as follows [23]:

$$P \propto f\ I^2 \tag{2.8}$$

Therefore, power consumption depends on the supply current and the frequency of changing between different modes. Reducing the current by applying a low sampling-rate procedure is a very effective way to reduce power consumption. Moreover, the lifetime of the power supply can be increased by reducing the current drastically or by regularly placing it in sleep mode, because the lifetime of power supply is related to the amount of its current drawn.

2.2.2.4. Communication unit

The communication unit consists of a receiver, transmitter, and an antenna. It is used in a WN to communicate with neighboring WNs and BS; as such it consumes a significant amount of power. An effective way to minimize the power consumption in the communication unit is to communicate data only when required and stay in sleep mode at all other times. There are other factors to do with power consumption in communication unit such as communication rate, transmission and reception power, and type of modulation. There are three methods to communicate data in a network, including Optical Communication (OP), Acoustic Communication (AC), and Radio Frequency (RF). Acoustic communication is used as a kind of transducer to transmit data encoded as sound waves in the WNs. The power consumption in these systems is low, but the size of the transducer limits its application. Optical communication systems are based on a laser beam to send data through the whole of the network. They can be categorized as optical active systems or optical passive systems. The optical passive system does not produce laser on board. It has a micro-electromechanical system corner-cube-reflector (MEMS CCR) to reflect or scatter the laser from the source, and power consumption for each node is between 20-100 pw. An external device is required to generate the beam and then receive and decode the data of nodes. In active optical systems, the laser beam generator is on board, and a message is transmitted by the laser to encode the data. The active optical is not transmitted in all directions, but it is focused with a small divergence. The divergence of the beam can be expressed as [24]:

$$\theta_d = 4\lambda / \pi\alpha \tag{2.9}$$

where α is the aperture diameter in meters and λ is the wavelength of the input signal between 300-750 nanometers. The power density in active optical system is equal to [24]:

$$\Upsilon = P_T / \Omega R^2 \tag{2.10}$$

where Ω and R are surface area distance from the transmitter to receiver nodes in meter and respectively, P_T is transmitter power. In RF systems, nodes communicate with themselves and other nodes via radio frequency and use the IEEE 802.11 protocol. Each WN must either expand data to listen to the signal and decide whether or not it was intended for them because it is not necessary to transmit over long a distance for most of the wireless nodes. The power management of smart receivers can be accomplished through collaboration with CS theory to establish low power RF systems. The transmitter power P_T is as follow [24]:

$$\Upsilon = P_T / 4\pi R^2 \tag{2.11}$$

where Υ is power density and P_T is transmitter power and R is the distance from the nodes. Noisy environment may cause a problem for receivers to distinguish data from noise. In that case, optical or acoustic communication needs to be considered. The combination of communication systems can lower network consumption by managing communication rates. The sleep mode has lower power than other modes in the communication unit. Thus it is important to change to sleep mode whenever it is not transmitting or receiving data. A key evaluation metric for any WN is its communication range. While we have made the argument that the coverage of the network is not limited by the transmission range of the individual nodes, the transmission range does have a significant impact on the minimal acceptable node density. If nodes are placed too far apart it may not be possible to create an interconnected network or one with enough redundancy to maintain a high level of reliability. Table 2.4 compares some parameters for a communication unit in a particular WSN with a range of 500 meters in active and sleep modes.

Table2.4: Parameters for a communication unit with 500 meters range

Parameter	Active mode	Sleep mode
Power consumption in receiving and transmitting	24.10 mw	0.001 mw
Amplifier power	23.2 mw	0.002mw
Transmutation rate	1.1 Mbps	0 Mbps

2.3. Overview of Wireless Body Area Networks

A WBAN as a subnet of WSNs consists of small, intelligent wireless sensors attached to or implanted in bodies and which are capable of establishing a wireless communication link [24, 25]. A schematic overview of WBANs and WSNs is given in Table 2.5.

Table2.5: Schematic overview of WBANs and WSNs

Parameter	Wireless Sensor Networks	Wireless body Area Networks
Scale	Monitor 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 replace	Impossible to replace 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

WBANs play an important role in remote patient monitoring, intelligent emergency care management systems, intensive care, surgery and intervention systems, diagnosis procedures, and ubiquitous wireless healthcare applications by moving wireless communication technologies to BANs or Personal Area Networks (PANs) for carrying the biomedical data. In the WBANs, the BWSs collect and transmit the vital signals of patients wirelessly to medical centers via GWs. The WBANs can also be used to offer assistance to the disabled [26, 27]. For example, a paraplegic can be equipped with wireless sensors determine the position of the legs or with wireless sensors attached to the nerves. In addition, electronic actuators positioned on the legs can stimulate the muscles. Interaction between the data from the wireless sensors and the electronic actuators makes it possible to restore the ability to move. Another example is aid for the visually impaired. An artificial retina, consisting of a matrix of micro wireless sensors, can be implanted into the eye under the surface of the retina. The artificial retina transfers the electrical signals into neurological signals. The input of network can be extracted locally by light sensitive wireless sensors or by an external camera located on glasses [28]. Moving wireless communication technologies to wireless healthcare systems for carrying the biomedical data adds another level the application of specific type of WSNs. Figure 2.8 shows specific types of wireless networks that are suitable models for transmitting the biomedical date from the human body to the hospital and medical centers [29].

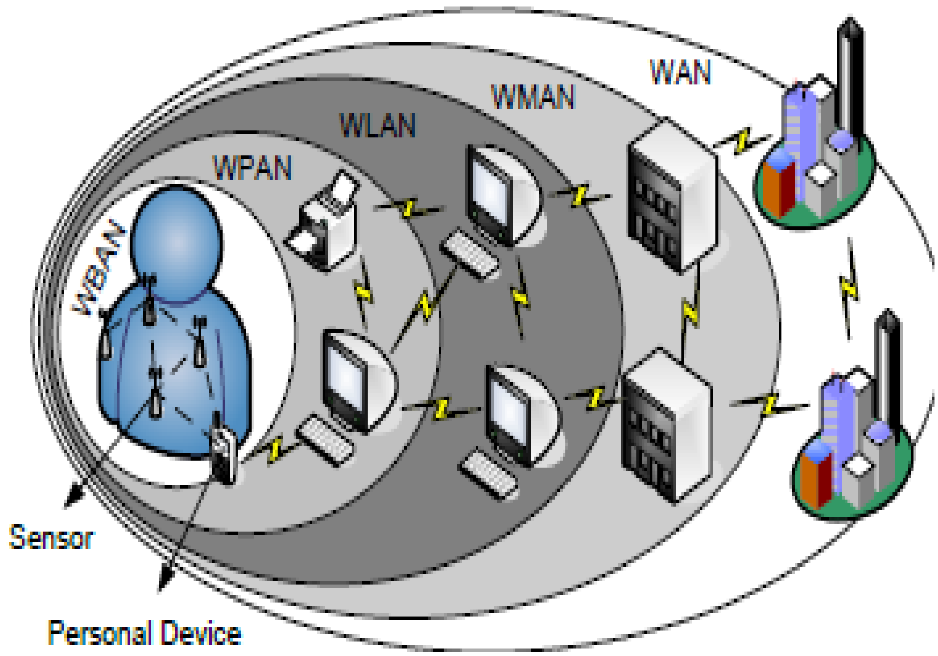


Fig.2.8: Specific types of wireless networks as an suitable background for WBANs [29]

The WBANs as one of the applications of WSNs are used to provide inexpensive and continuous health monitoring systems with a real-time update of medical records via the Internet [30]. The WBANs are responsible to collect, process, and transmit important information of vital signals of patients such as blood pressure, brain, heart, tissues and neurons of the body to medical centers to provide inexpensive and continuous health monitoring systems. In the WBANs a coordinator such as a smart phone or Personal Digital Assistant (PDA) collects and distributes these data wirelessly to medical centers [31]. Medical applications of WBANs cover continuous waveform sampling of biomedical signals and monitoring of vital signal information. They also perform vital medical data-acquisition, data processing, data transmission, and provide some basic user feed-back. The increasing use of wireless network and the constant miniaturization of the electronic device have empowered the development of WBANs in wireless monitoring. We are now going to a step further by becoming IH, MH, and EH. Among various constraints in designing such systems, the three important constraints are energy consumption, data compression, and device cost. By this convenient means, people can keep track of their health condition without frequent visits to their doctors [32]. AWBAN could allow a patient to store its collected data on his/her PDA or smart phone or any other portable device and then transfer that information to the external database. The WBANs give patients greater mobility and increased comfort by freeing them from the need to be connected to hospital equipment that would otherwise be required to monitor their conditions [33]. This improves the quality of patient care and the efficiency of hospital administration capabilities. Moreover, WBANs also serve the goal of reducing health care costs because they permit the remote monitoring of several patients simultaneously. Today a number of wireless communication technologies are available. Typical short-range solutions are Bluetooth, Zig Bee, and WPAN. Several of these solutions are for short-range within 10 meters and are reasonably power efficient [34]. Figure 2.9 describes the power consumption versus data rate spectrum for different types of Wireless networks.

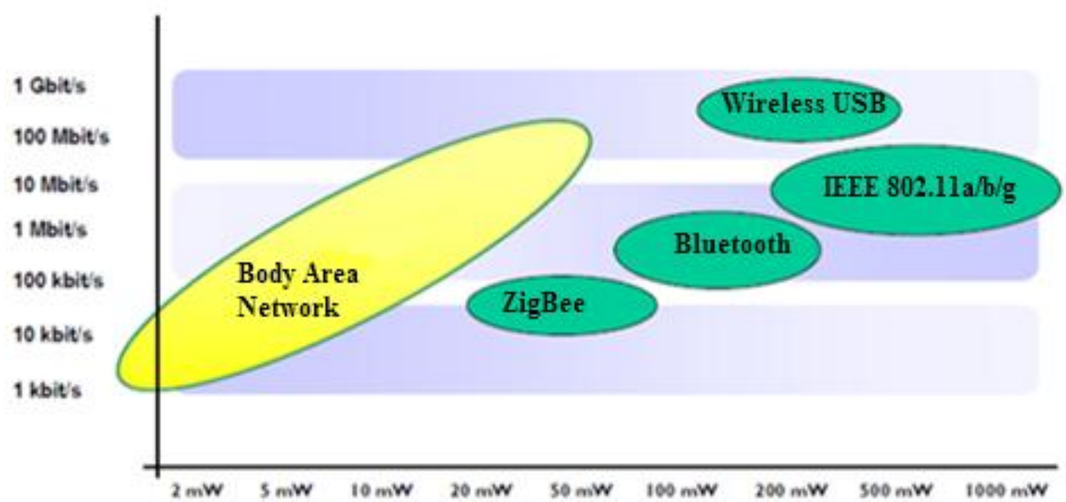


Fig.2.9: Data rate versus power consumption

As we can see, the range of WBANs devices can vary significantly in terms of the bandwidth and power consumption. Moving wireless technologies into BANs or PANs for carrying the biomedical data is adding another level of quality of life for patients [35]. Figure 2.10 illustrates wireless technologies in terms of data rate.

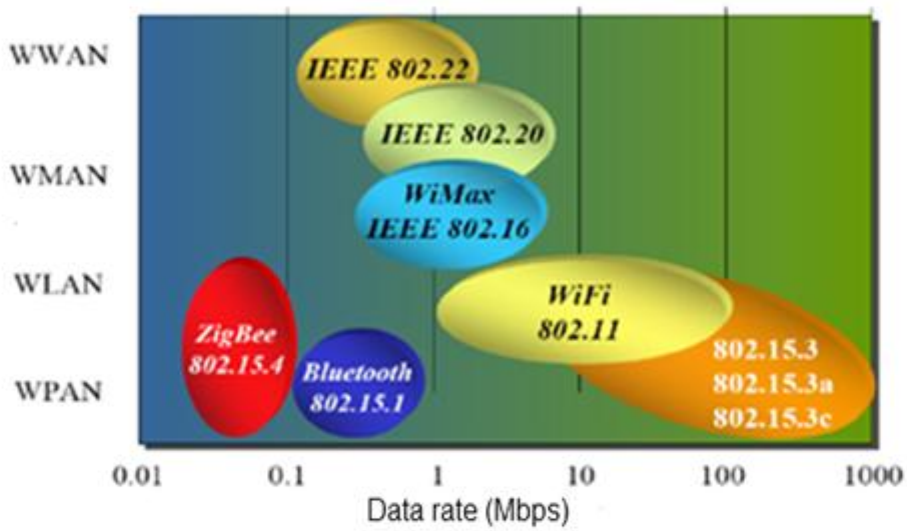


Fig.2.10: Wireless technologies in terms of Data Rate [22]

Based on a biomedical input signal from the BWSs the wireless communication technology requirements have been specified. In the WBANs several applications require only low bandwidth ($\leq$ 10 kb/s) and by reducing the rate of sampling it is possible to increase battery life and improve security/robustness. Self-organizing and self-maintaining networks are designed by employing the effective sampling method. Regarding the propagation of electromagnetic (EM) waves in the human body, the BWSs provide signals to process and transmit through the network. In WBANs, the body acts as a communication channel, and BWSs act as transmitter or receiver [36]. For example, tissue losses are mainly due to absorption of power, which is dissipated as heat. For a problematic tissue, the amount of water is more or less than that of normal tissue, and then the attenuation of the EM-waves are changed to compare with a normal case in order to detect any problem before they are reached by the receiver. By comparing the amount of attenuation power with the 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 the power is observed in tissue is used: the Specific Absorption Rate. The interaction with the user or other persons is usually handled by a PDA or smart phone, which acts as a sink wireless node [37]. Figure 2.11 shows an example of intra-body and extra-body communication in a WBAN with PDA.

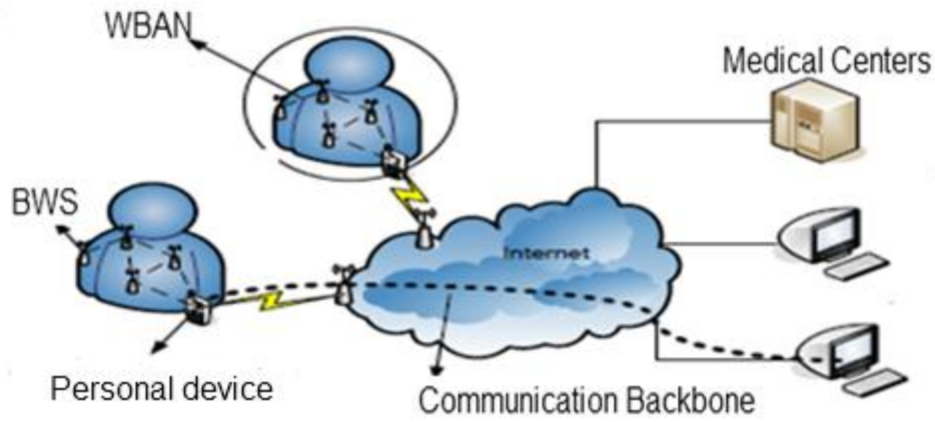


Fig.2.11: Example of intra-body and extra-body communication in a WBAN with PDA

Due to the strong heterogeneity of the applications of WBANs in practice, data rates will vary strongly, ranging from simple data at a few Kbps to video streams of several Mbps [37, 38]. Table 2.6 provides some important characteristics of medical applications such as data rate, bandwidth, and accuracy.

Table2.6: Characteristics of biomedical signals

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

In the above table, ECG is a transthoracic interpretation of the heart over a period of time. The EEG is recording of electronic activity along the brain. The EMG is a system for evaluating and recording the electrical activity produced by skeletal muscles. Overall, it can be seen that the application data in WBANs fall between 16 bps to 1 Mbps. The reliability of the data transmission is provided in terms of the necessary Bit Error Rate (BER), which is used as a parameter for the number of packets [39]. For medical devices, the reliability depends on the data rate. The low transmission rate devices can cope with a high BER, while a higher transmission rate requires a lower BER. The required BER is also dependent on the criticalness of the data. The ideal WBANs must be designed to accommodate micro-power generation and storage, ultra-low-power radio communication and low-sampling rate. In most cases, they will be set up in a hospital by medical staff. Consequently, they should be capable of configuring and maintaining themselves [40]. They need a security procedure to make medical decisions with high accuracy. The intelligent physiological BWSs can be integrated into a wearable body area network, which can be used for computer-assisted rehabilitation or early detection of medical conditions.

2.3.1. Applications of WBANs

In WBANs miniaturized BWSs are attached on clothing or on the body or even implanted under the skin to sense and transmit biomedical information. They hold the promise to be a key enabling information and communications technology for next-generation, patient-centric, telemedicine, and mobile cardiology solutions. Figure 2.12 shows that WBAN is responsible to sense, collect, and communicate the vital signals such as blood pressure, heart-rate, ECG, EEG, tissues and neurons of the human body in the near future [41]. The biomedical measurements can be recorded over a longer period of time to improve the quality of the measured data. Furthermore, they are used to measure certain parameters of the human body, either externally or internally.

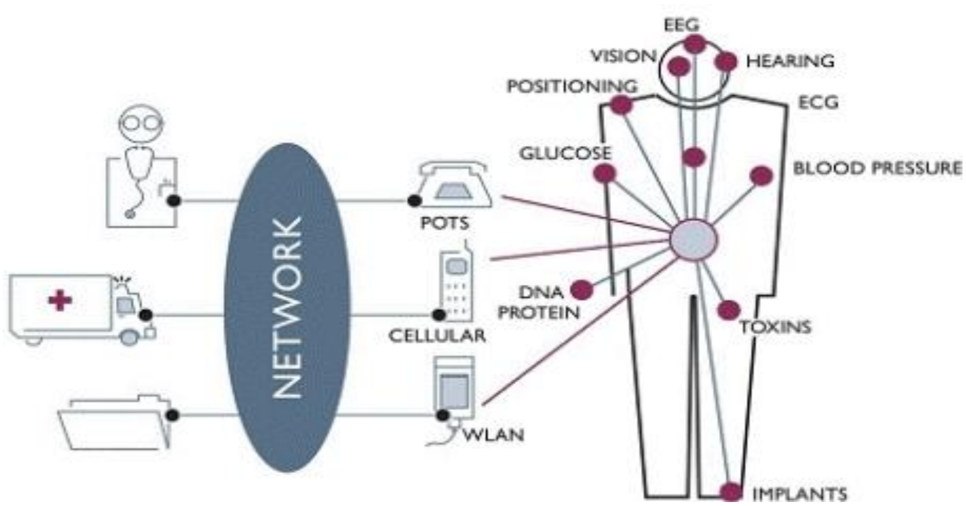


Fig.2.12: Biomedical signals in WBANs [41]

Figure 2.13 shows this possible scenario for next generation using wireless healthcare systems [42].

Fig.2.13:Saving hope with wireless healthcare systems [42]

As we can see in Fig.2.13, the main architecture consists of two basic parts: multiple Wireless Body Sensor Units (WBSUs) and a Wireless Body Center Unit (WBCU). The WBSUs acquire vital medical data process and transmit data and also provide some basic user feedback. The WBCU links multiple sensor units, performs data collection, data compression and event management [43, 44]. Afterwards the physiological information will be transmitted wirelessly to the medical center. If an emergency is detected, the physicians will immediately inform the patient by sending appropriate messages through WSNs. Figure 2.14 shows several applications of WBANs [45].

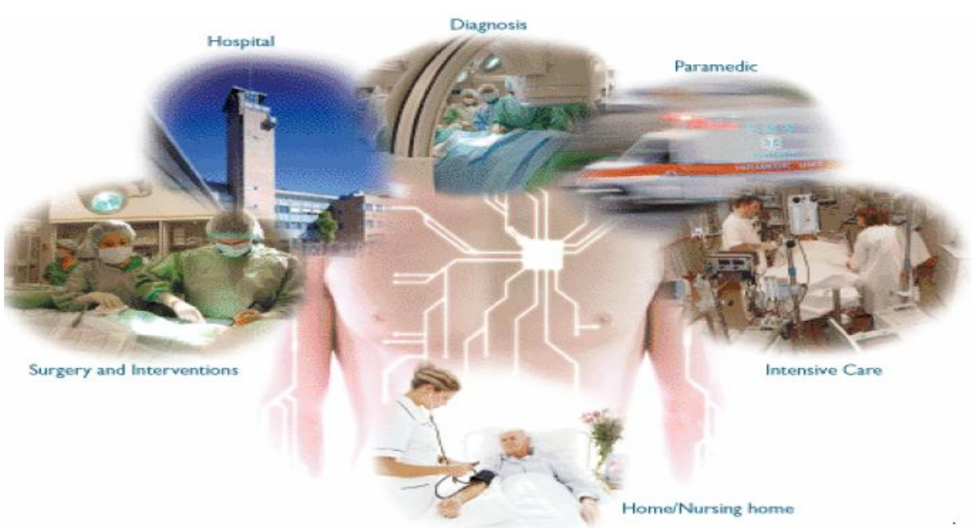


Fig.2.14: Applications of WBANs [44]

2.4. Relation between Wireless Networks and WBANs

The collected and compressed biomedical data by BWSs need to be transmitted to medical centers for medical purposes via specific wireless networks, such as WPANs and WLANs for inside hospitals and WMANs for urban areas. The Wireless Wide Area Network (WWAN) can be used for transmitting compressed biomedical data anywhere. Figure 2.15 shows a collaboration of WBANs via specific wireless networks for sending compressed biomedical data at anytime and anywhere. The benefits are removing the constraints of time and location of patients while increasing both the coverage and quality of healthcare services.

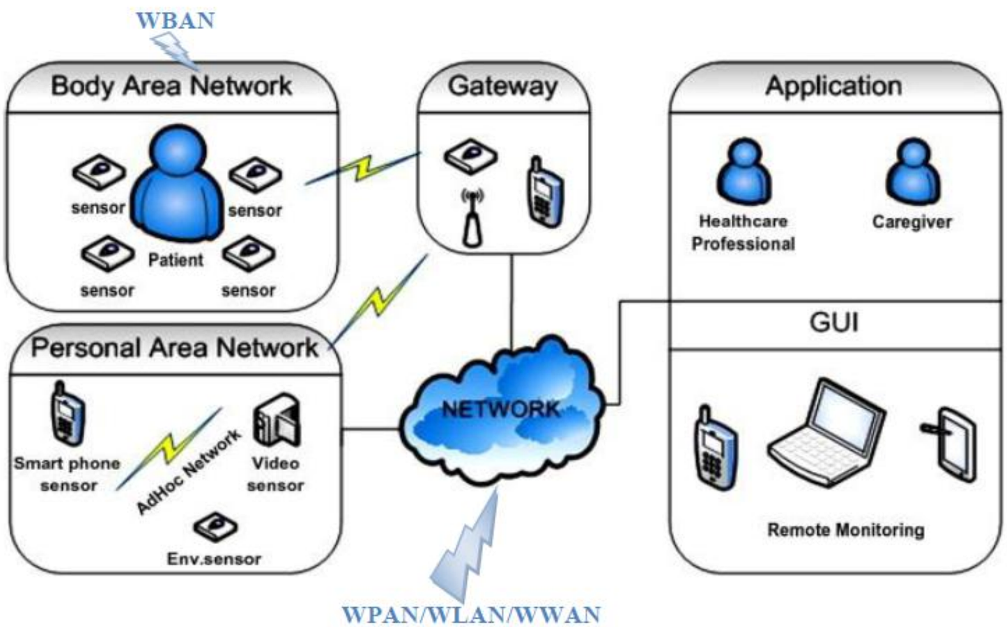


Fig.2.15: Contribution of WBANs and wireless networks

In the WBANs the small, intelligent BWSs are responsible to collect, process, and transmit vital information from the human body. The collected biomedical data should be transmitted to APs in medical centers via a specific type of specialized wireless networks such as WPAN, WLAN, and WMAN. IEEE 802.15 supports WBANs for low-power operation in or around the human body (but not limited to the human body) to serve a variety of applications [46, 47]. It operates from 2.4 MHz to 2483 MHz. The protocol employs a frequency-hopping multiple access scheme to combat interference and fading. A specific type of IEEE protocols could be used to design WBAN for medical and other health monitoring applications. The main objective of the

IEEE802.15 standard is to provide a low-cost, reliable and low-power wireless communication to support a range of WBANs and home networking solutions [49]. The IEEE has also launched IEEE 820.15 task group 6 for Body Area Networks (BANs) and Body Sensor Networks (BSNs) to develop a communication standard optimized for low-power devices and that operate on, in or around the human body to serve a variety of applications [50]. In this research, we want to use IEEE802.15.1 to combat interference. The IEEE802.15.1 operates in the 2.4 GHz from 2400 MHz to 2483.5 MHz. Based on this standard, the symbol rate in our schemes is 2 M symbol/s supporting a bit rate of 1.1Mb/s. Figure 2.16 shows the contribution of the CS theory, WBANs, and specific types of wireless networks. Figure 2.17 shows IEEE protocol in WBANs with regards to the destination of biomedical data.

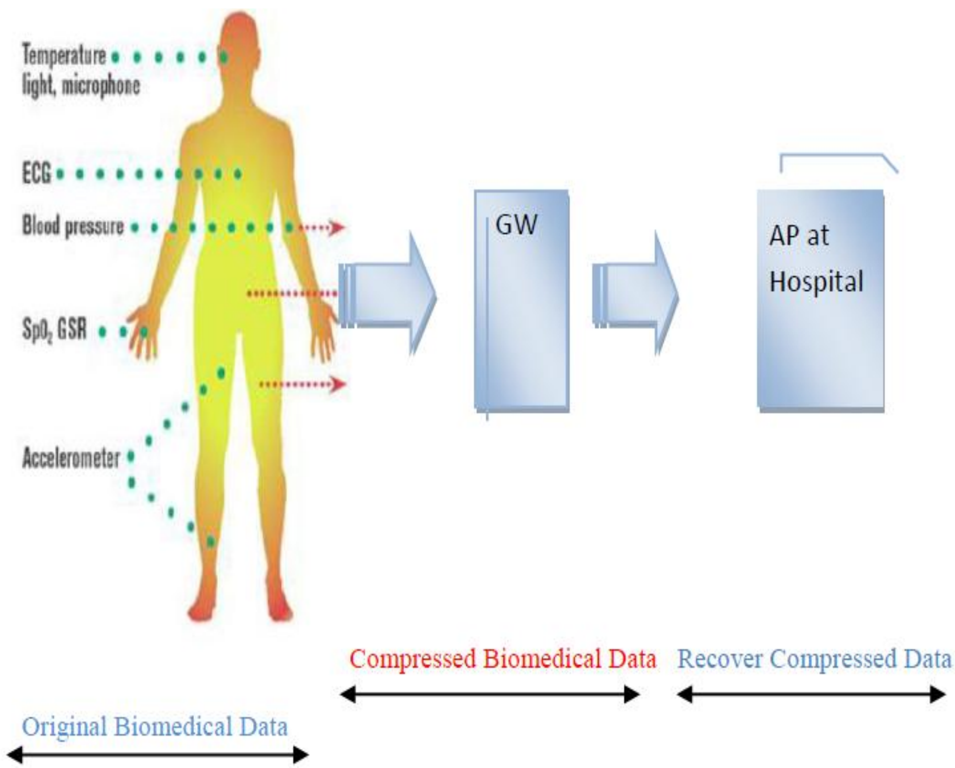


Fig.2.16: Operation of WBANs and wireless networks based on CS theory

As shown, the biomedical signals are compressed by BWSs. The collected compressed biomedical data are then transmitted wirelessly to APs at the hospital, ambulance, and helicopter for recovering the original data. The APs are recovered compressed biomedical data for diagnostic and therapeutic purposes.

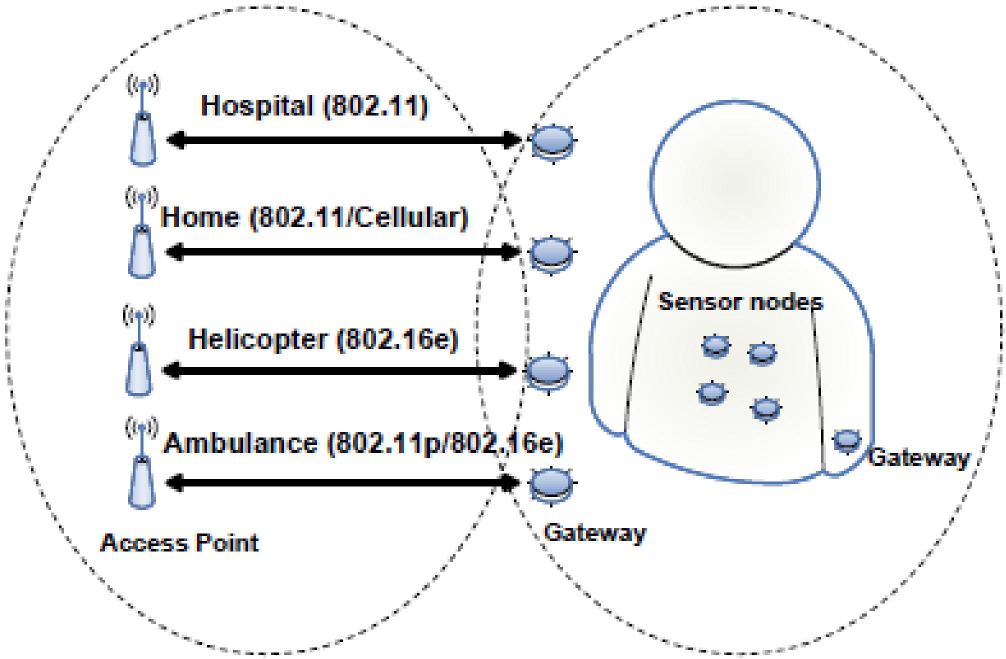


Fig.2.17: IEEE protocols for medical applications

2.5. Chapter Summary

In this chapter, the WSNs and wireless healthcare systems or WBANs are presented. This chapter also explained that WSNs suffer from significant problems, such as limited processing capability, limited storage capacity, size, and power. We also discussed that the current healthcare systems are restricted by size, patient's mobility, power, and transmission capacity. Among various constraints in designing wireless healthcare systems, three important constraints are energy consumption, data compression, and device cost. This chapter emphasized that current healthcare systems need to be further developed in order to achieve the following objectives; extended mobility for patients inside or outside of the hospital and medical centers, monitoring of several patients at the same time, and further adaptations by medical experts. New wireless healthcare systems based on CS theory could give patients greater mobility and increased comfort by freeing them from the need to be connected to hospital equipment that would otherwise monitor their conditions. This improves the quality of patient care and efficiency of hospital administration. Moreover, wireless healthcare systems based on CS theory also serve the goal of reducing health care costs because they permit the remote monitoring of several patients simultaneously. In the next chapter, the CS theory as a new and low sampling-rate is illustrated in order to improve the constraints of WBANs such as patient's mobility, cost, size, and single monitoring.

2.6. Plan for next Chapter

In the next chapter, we confirm that a contribution from CS theory and WBANs is the optimal solution for achieving autonomous wireless medical networks with low-power and low sampling-rate. Sensing and processing biomedical data have traditionally relied on the Shannon Sampling theorem. This theorem sates that, given a signal of bandwidth Ω, it is sufficient to sample at 2Ω samples per second to ensure faithful representation and reconstruction. The traditional approach has been found inadequate lately. First, in many signals Ω is so large that the Nyquist-rate is unbearable. Second, even for low signal bandwidths such as ECG signals, the traditional approach produces a large amount of redundant digital samples, which are costly for wireless transmission and severely limit the biomedical wireless sensor's lifetime. The CS theory reduces the load of sampling by merging the sampling and compression steps together. The basic idea of CS theory is that when the biomedical signal is sparse in terms of the number of non-zero coefficients or the number of non-zero blocks, relatively few well-chosen observations suffice to reconstruct the original signal. Rather than measuring each sample and then computing a compressed representation, CS theory suggests that we can measure compressed representation directly. CS is a new approach for the acquisition and recovery of sparse signal either on the number of non-zero coefficients or the number of non-zero blocks that permits sampling-rate significantly below the classical Nyquist-rate. Figure 2.18 illustrates the plan for next chapter. As it is depicted in Fig.2.18, the following concepts are presented in the next chapter:

►Define a general description of CS theory.

►Present a list of problems with the conventional sampling methods.

►Demonstrate general block diagram for CS theory.

►Divide CS theory into two main compression and reconstruction steps.

►State important conditions for the success of CS theory.

►Verify CS theory in wireless networks and biomedical wireless networks.

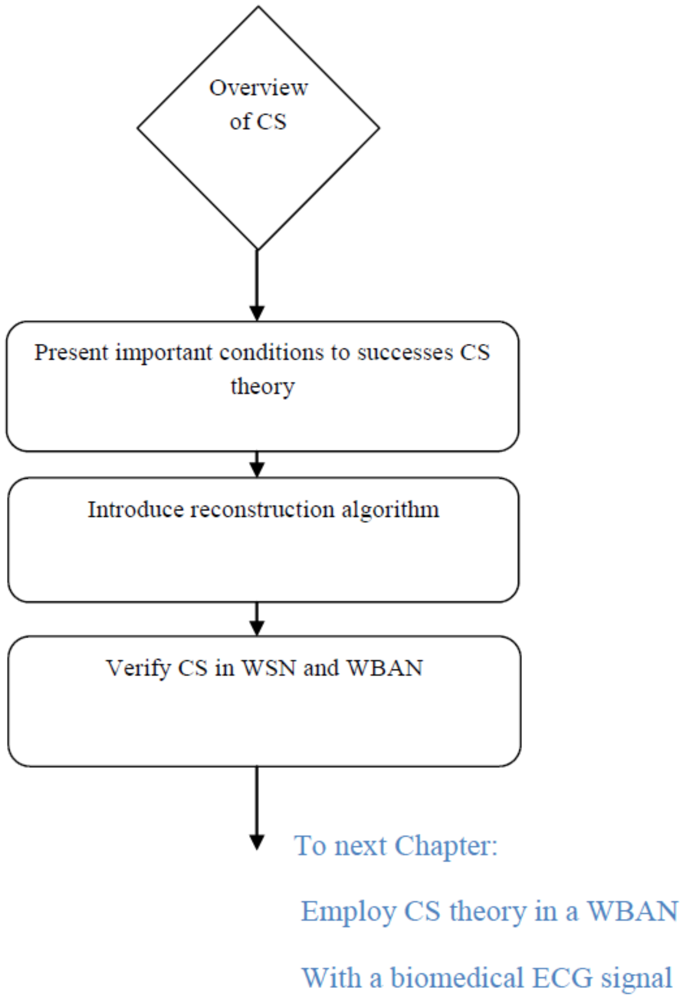


Fig.2.18: Plan for next chapter

Chapter 3

Literature Review of CS and Verification in WBANs

3.1. Motivation

The conventional sampling approaches have traditionally relied on the Shannon sampling theorem. This theory says a signal must be sampled at least twice its bandwidth in order to be represented without error [51, 52]. The traditional approaches have two major drawbacks. First, they generate huge intolerable samples for many applications with a large bandwidth. Second, even for low signal bandwidths including, some biomedical signals, they produce a large amount of redundant digital samples. That is why it is desirable to reduce the number of acquired biomedical samples by utilizing sparsity [53, 54]. The main motivation is to replace the conventional sampling and reconstruction operation with a general random linear measurement process and an optimization scheme in order to recover the original signal from a small number of random measurements. In this chapter, we first discuss the CS theory as a new sampling method. Second, we explain the reconstruction method to recover the original signal at the receiver side. Figure 3.1 shows our plan in this chapter.

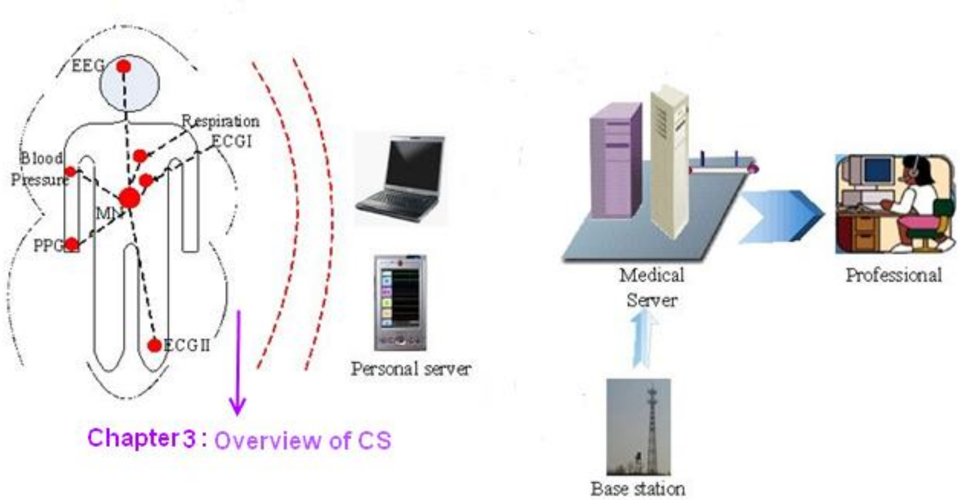


Fig.3.1: Plan for this Chapter

3.2. Basic Theorem

CS is a new approach for the acquisition and recovery of sparse signals either from the number of non-zero coefficients or the number of the non-zero blocks that enables a sampling-rate significantly below the classical Nyquist-rate. CS theory presents a novel signal measuring approach using compressed sensing method. This theory states a small number of random linear measurements of compressible signals contain enough information to recover and process the original signal [55]. Furthermore, the signal representing sparsity in any orthogonal basis can be well recovered using a small number of random measurements. This idea is attracting many talented researchers in areas like Information Technology (IT), Optimization Procedures and Mathematical Statistics [56]. A basic block diagram of the CS scheme is provided in Figure 3.2.

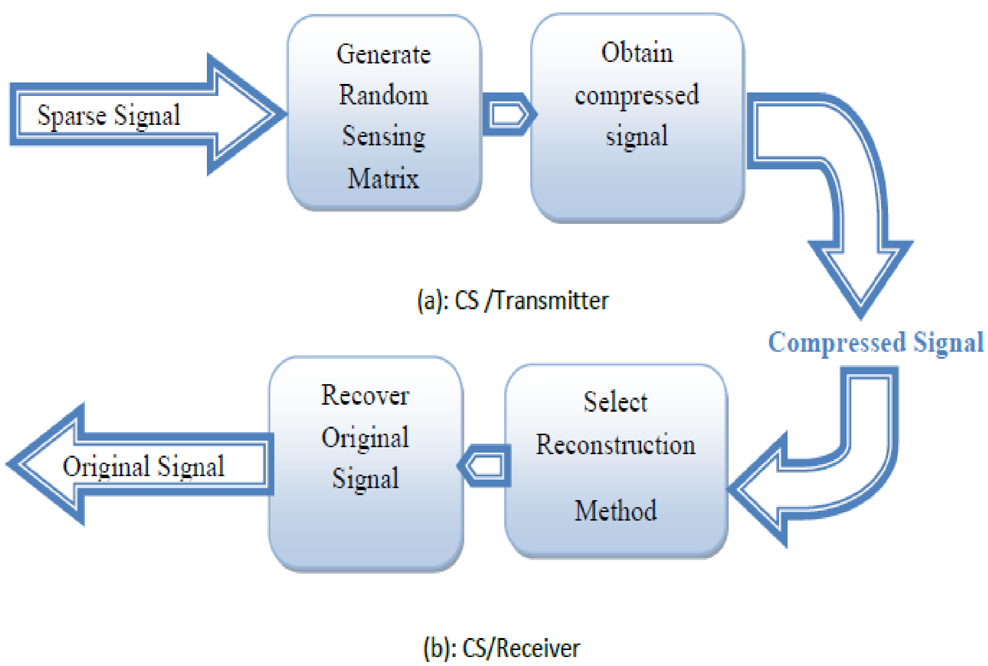


Fig.3.2: (a) A block diagram of CS in transmitter. (b) A block diagram of CS in receiver

Sensing and processing biomedical data have traditionally relied on the Shannon Sampling theorem. This theorem states that, given a signal of bandwidth Ω, it is sufficient to sample at 2Ω samples per second to ensure faithful representation and reconstruction. The traditional approach has fallen short lately. First, in many signals Ω is so large that the Nyquist-rate is unbearable. Second, even for low signal bandwidths such as some biomedical signals, the traditional approach produces a large amount of redundant digital samples, which are costly for wireless communication and severely limit the biomedical wireless sensor's lifetime. Therefore, traditional approaches have two major drawbacks: they generate a huge and intolerable number of samples for applications with large bandwidth and a large amount of redundant digital samples for low bandwidth signals [57, 58]. The CS theory makes the most of the fact that many natural signals are sparse or compressible in the sense that they have concise representations when expressed in the proper basis. The fundamental purpose of CS theory as a new sampling scheme is to reduce the number of measurements required to completely define a signal by exploiting its compressibility. The CS theory has shown that sparse signals in terms of either a small number of non-zero coefficients or a small number of non-zero blocks can be accurately represented as random linear combinations of a few projections of such signals in data-independent random vectors. The general linear measurement process computes the inner product between original signal and a random sensing matrix. The biomedical signal of interest does not have to be sparse in the original domain; it may be sparse in some other domains such as the frequency domain or in Discrete Cosine Transform (DCT) domain [58]. CS theory allows for efficient and direct compression of a sparse biomedical signal. An important aspect of CS theory is that elements of random sensing matrix Φ are linear combination from measurements of the signals. Any compressible signal or sparse signal *D* in R^N can be expressed in terms of a suitable basis of $N \times 1$ vectors $\{\Psi_i\}$ such that $1 \le i \le N$. Forming the $N \times N$ basis matrix $\Psi = [\Psi_1, \Psi_2, ...\Psi_N]$ by stacking the vector $\{\Psi_i\}$ as columns, the compressible signal *D* can be represented like [59]:

$$D = \sum_{i=1}^{N} S_i \Psi_i \tag{3.1}$$

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 $N \times 1$ vectors $\{\Psi_i\}$. On the other hand, any compressible signal has few large coefficients and a many number of small coefficients. That is why any compressible or sparse signal has *K* non-zero coefficients and *(N-K)* Zero coefficients with $K \ll N$. The sparsity is determined by the fact that many natural signals are compressible in the sense that a basis Ψ exists where the representation shown in Eq. (3.1) has just a few large coefficients and many small coefficients and they are well approximated by K-sparse representations [60, 61]. As a result, the compressible signal D is a linear combination of just K basis vectors, with $K \ll N$ and is approximated by only K-sparse representation. Nevertheless, compressible signals such as data networks, data of WSNs, data of digital images, data of biomedical systems, and data of A/D invertors have K nonzero coefficients, but their location is unknown.

The flowchart for the current sampling methods is shown in Figure 3.3.

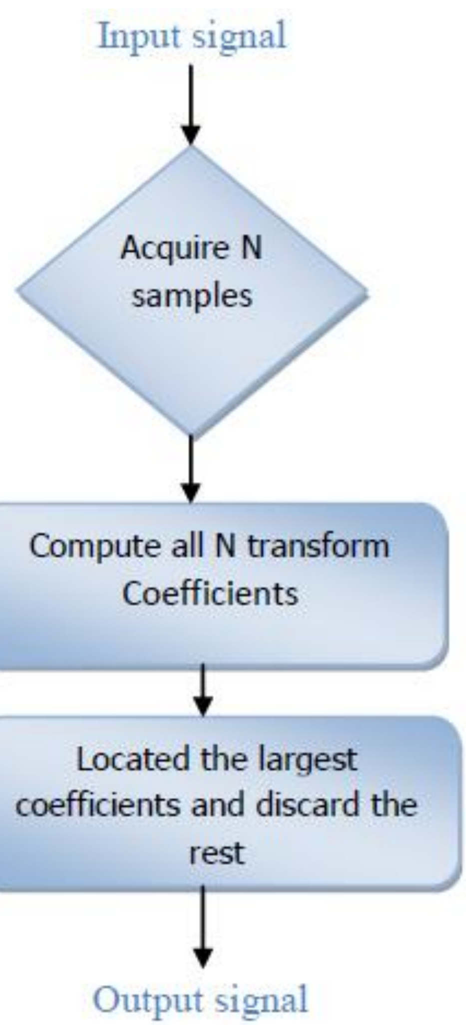


Fig.3.3: Flowchart for the current sampling methods

Therefore, current sampling methods have the following steps in order to determine the location of non-zero coefficients:

►Acquire the full number of samples.

►Compute the complete set of transform coefficient {S_i} via $S = \Psi_i^T D$.

►Locate the *K* largest coefficients and discard the (*N*-*K*) small coefficients using the adjustable threshold value.

►Encode the *K* values and location of the largest coefficients.

►Convert the values and locations to digital bits.

Consequently, the current sampling methods suffer from an inherent inefficiency, because in order to find the location of nonzero coefficients, they must start and compute with a potentially large number of samples *N* even if the ultimate desired *K* is small and the encoder must compute all of the *N* transform coefficients {S_i} even though it discards (*N* - *K)* of them [62, 63]. Therefore, the encoder faces the overhead of encoding the locations of the large coefficients. Thus, the systems that are using the current sampling methods have the same problems of global traffic, high power consumption, limited processing capability and low storage capacity.

Over the past few years, the CS theory as a new sampling method has emerged to reduce sampling rate and global traffic for sparse signals. The CS theory changes information of the large samples to a few numbers of the linear random measurements of all point in the compressed signal [64]. The CS is an advanced signal and image processing approach and presents the links between data acquisition, linear algebra, optimization and random processes. In fact, the CS theory offers stable measurements metrics with *M* independent and identically distributed (i.i.d) elements of the compressed signals such as $K \le M \ll N$ [65]. The CS theory also guarantees recovery of the original signal from the compressed signals under certain conditions and enough accuracy and high probability from the compressed signal with only *M* random measurements. As an excellent alternative, CS theory allows us to focus on *M* linear measurement between the original signal *D* and a collection of events $\{\Phi_j\}_{j=1}^{M}$ to generate $\mathbb{C} = \langle D, \Phi_j \rangle$ with general linear measurement process that computes $M \ll N$ inner products between *D* and a collection of vectors $\{\Phi_j\}_{j=1}^{M}$. We can generate the compressed signal $\mathbb{C}$ with measurements $\mathbb{C}_j$ into the $M \times 1$ vector and the measurements vectors Φ_j^T as rows into an $M \times N$ matrix Φ. Our goal in using CS theory to obtain a new sampling scheme for digital signals is to reduce sampling-rate by decreasing the number of samples required to completely describe a signal through compressibility [66]. An important aspect of CS theory is that our measurements are not point samples; rather they are more general linear function of the signals [67]. In digital-CS theory, any compressible or sparse signal D in $\mathbb{R}^N$ can be expressed like [68]:

$$D = \sum_{i=1}^{N} C_i \Psi_i \tag{3.2}$$

Therefore, the compressed signal $\mathbb{C}$ is found as:

$$[\mathbb{C}]_{M\times 1} = [\Phi]_{M\times N}[D]_{N\times 1} \tag{3.3}$$

Thus, the compressed signal is found as:

$$[\mathbb{C}]_{M\times 1} = [\Phi]_{M\times N}[\Psi]_{N\times N}[C]_{N\times 1} = [\Theta]_{M\times N}[C]_{N\times 1} \tag{3.4}$$

$[\Phi]$ and $[\Theta]$ have two interesting and useful properties. First, they are incoherent with the basis $[\Psi]$. Second, they have the Restricted Isometry Property (RIP) with accurate level for detection probability of the compressed signals at the receiver side that is suitable for recovering the original signal from compressed signal [69]. Thus, CS scenario has two important steps. The first step offers a stable measurement matrix $[\Phi]_{M\times N}$ 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 $\mathbb{C} \in \mathbb{R}^M$ [70]. In the second step, the CS theory offers a reconstruction algorithm under certain conditions with enough accuracy to recover, original signal D from the compressed signal [56]. The signal representing sparsity in any orthogonal basis can be well reconstructed using ℓ_1 norm minimization, while satisfying the RIP condition for the random measurements matrix Φ, which is offered by compressed sensing theory and orthogonal base Ψ in any domain. Therefore, we can exactly reconstruct, with a very high level of accuracy, the original signal D with high probability via ℓ_1 by solving the following convex optimization problem ($\| D \|_1 = \sum_n |D_n|$) [71]:

$$\min_{D \in \mathbb{R}^N} \| D \|_1 \text{ subject to } \mathbb{C} = \Phi D \tag{3.5}$$

However, certain conditions must be met to guarantee the accuracy of the recovery [58, 59]. First, the number of random linear measurements, coefficients, and non-zero coefficients must satisfy the following equation [72]:

$$M \leq K / C(\log N) \tag{3.6}$$

where C is constant and M, N, and K are the number of random measurements, the total of coefficients, and the number of non-zero coefficients respectively.

Second, for any vector a of the original signal $[D]$ matrix $[\Phi]$ must satisfy the following condition for some of $\varepsilon \succ 0$:

$$1-\varepsilon \le \|\Phi\alpha\|_2 / \|\alpha\|_2 \le 1+\varepsilon \tag{3.7}$$

where it satisfies RIP for the random dictionary matrix. In order to recover *K-sparsity* of the original signal, now we have $M \times K$ system of linear equations, with M equations and K unknowns, and since $M \ge K$, it is possible to find the *K-sparsity* of the original signal [73]. As an example, Figure 3.4 shows how compressed signal can be generated from the original signal D [74].

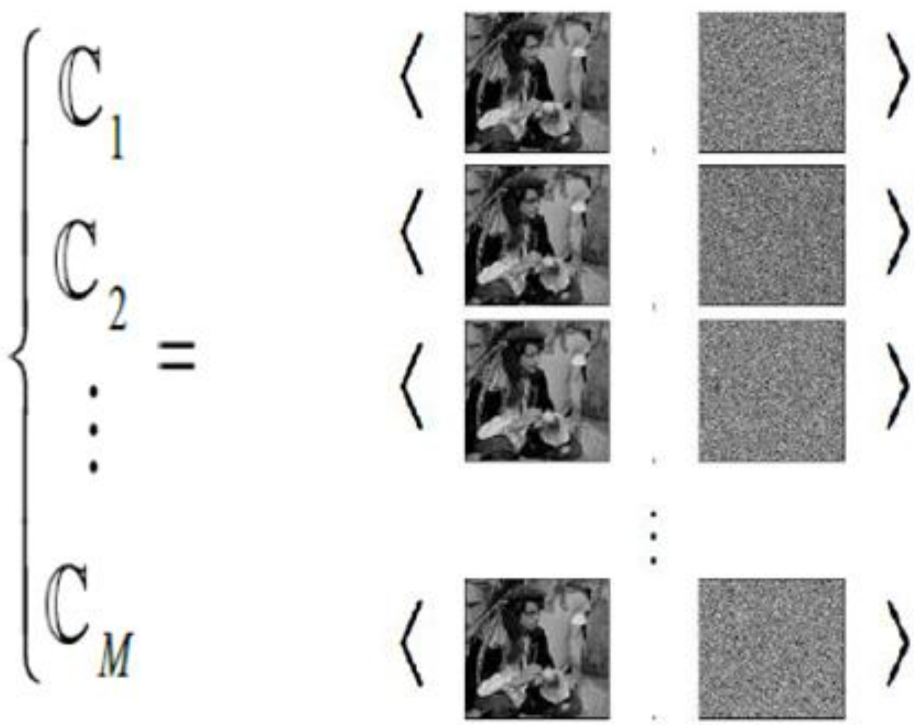


Fig.3.4: Steps to generate compressed signal

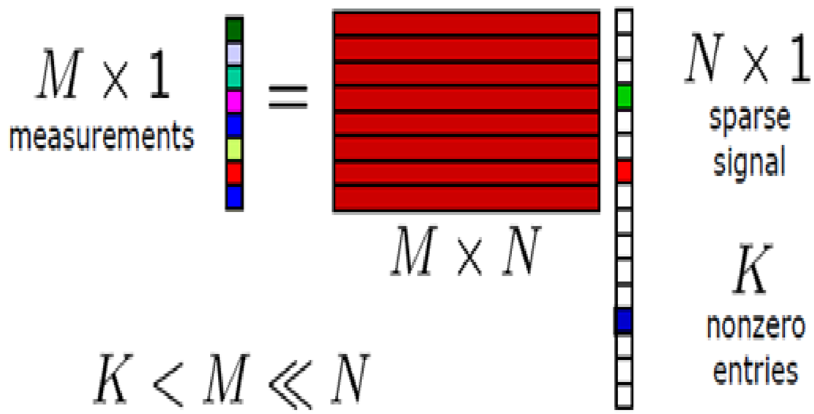
The received signal can be written as:

$$[\mathbb{C}]_{M\times 1} = [\Phi]_{M\times N}[D]_{N\times 1} \tag{3.8}$$

Consequently, the received signal is a condensed representation of the sparse events and can be expressed as:

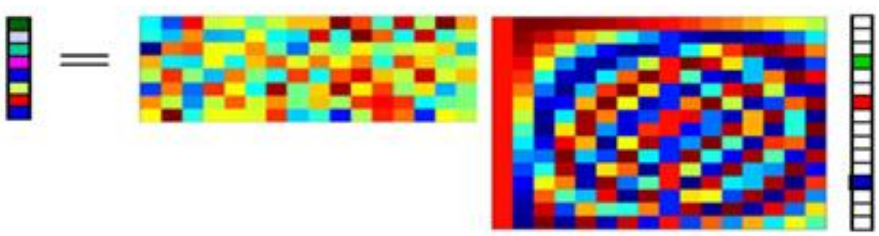
$$\begin{pmatrix} \mathbb{C}_1 \\ \vdots \\ \mathbb{C}_M \end{pmatrix} = \begin{pmatrix} \Phi_{11} & \cdots & \Phi_{1N} \\ \vdots & \vdots & \vdots \\ \Phi_{M1} & \cdots & \Phi_{MN} \end{pmatrix} \begin{pmatrix} D_1 \\ \vdots \\ D_N \end{pmatrix} \tag{3.9}$$

Figure 3.5 shows the scheme of CS theory with a pictorial depiction of Eq. (3.8), and Figure 3.6 shows a pictorial structure of Eq. (3.9). The matrix Φ is a $M \times N$ matrix such that $K \le M \ll N$. Surprisingly, the matrix Φ does not depend in any way on the original signal D and also has independent and identically distributed (i.i.d) random variable components.



$[\mathbb{C}]_{M\times 1} =$ $[\Phi]_{M\times N}$ $[D]_{N\times 1}$

Fig.3.5: Pictorial Scheme of CS theory



$[\mathbb{C}]_{M\times 1} =$ $[\Phi]_{M\times N}$ $[\Psi]_{N\times N}$ $[S]_{N\times 1}$

Fig.3.6: A Pictorial structure of Eq.3. 9 to generate compressed signal

Therefore, in the CS scenario we can focus only on M random linear measurements instead of N samples such that $M \ll N$. The CS theory also offers a reconstruction algorithm to recover original signal D from the compressed signal $\mathbb{C}$ only with M random linear measurements [75].

The CS theory consists of the following steps:

►Design a stable measurements matrix Φ.

►Develop a reconstruction algorithm to recover the original signal from the compressed signal in the receiver side.

► Test the number of *M* measurement to ensure that reduction from $\mathbb{R}^N$ to $\mathbb{R}^M$ is not damaged to recover the original signal.

To summarize, CS scenario has two major steps. First, it offers a random sensing matrix that ensures the salient information in any compressible signal is not damaged by the dimensionality reduction from $D \in \mathbb{R}^N$ into $\mathbb{C} \in \mathbb{R}^M$. In the second step, the CS theory offers a reconstruction algorithm under certain conditions with enough accuracy to recover original signal *D* from compressed signal $\mathbb{C}$. Figure 3.7 emphasizes that CS theory transfers $\mathbb{R}^N$ to $\mathbb{R}^M$ by sensing matrix Φ.

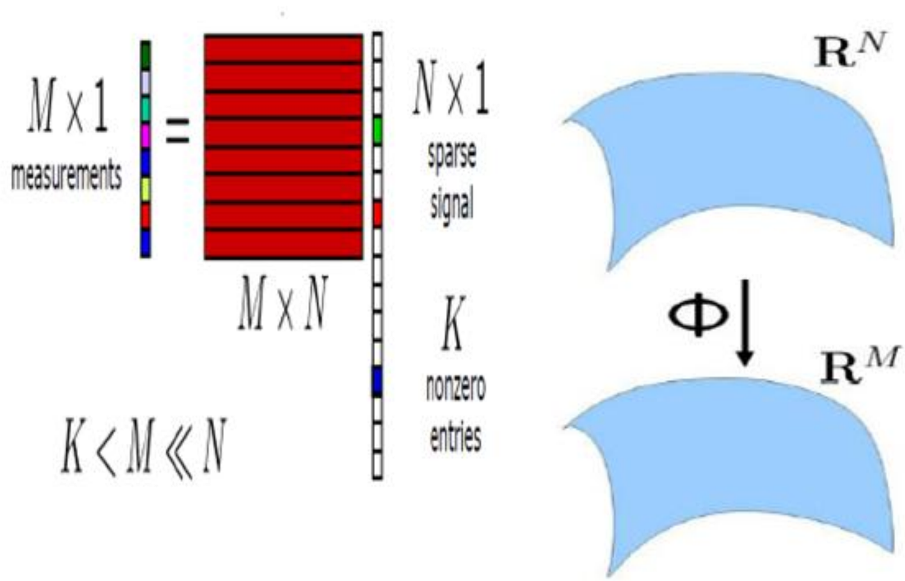


Fig. 3.7: Transferring space from $\mathbb{R}^N$ to $\mathbb{R}^M$ by sensing matrix Φ

3.2.1. Stable Sensing Measurement Matrix

The fundamental purpose of CS in the first step is to make *M* measurements, by which we can safely reconstruct the length-*N* of original signal *D*. It is very important that the reconstruction method be able to recover the information in original signal *D*. If the measurement process damages the information in *D*, the reconstruction scheme would not be able to recover the original signal D on the receiver side [76]. Now we have $M \times K$ system of linear equations to solve for nonzero entries, with *M* equation and *K* unknown such that $M \geq K$. A necessary condition to ensure that $M \times K$ systems support a stable reconstruction algorithm is in the form of [77]:

$$1-\varepsilon \le \left\|\Theta Z\right\|_2 / \left\|Z\right\|_2 \le 1+\varepsilon \tag{3.10}$$

The above equation is defined for any vector *Z* sharing the same *K* nonzero entries in $[S]_{N\times 1}$. For the practical signals, such as biomedical ones, we must select 3*K*- sparse vector *Z* for $[\Theta]$ to satisfy (5) in order to design a reconstruction algorithm with high accuracy [68]. This is called the RIP property. To generate a compressed signal we select $[\Phi]_{M\times N}$ as a random sensing matrix with i.i.d elements, each one with zero-mean and *1/N* variance [78]. Surprisingly, the compressed signal has *M* different randomly weighted linear combinations of the elements of the original signal *D*. The $[\Phi]_{M\times N}$ matrix has the following interesting properties:

►The $[\Phi]_{M\times N}$ matrix is incoherent with the basis $\Psi = I$ 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 random sensing matrix for every possible Ψ.

►The $[\Theta]_{M\times N} = [\Phi]_{M\times N}[\Psi]_{N\times N}$ matrix has the RIP with high probability.

Therefore, we can expect to recover length-*N*, *K-sparse* and original signal *D* with high probability from just *M* random measurements. Thanks to the properties of the i.i.d distribution, it is possible to generate the Θ matrix regardless of the choice of (orthogonal) scarifying basis of

matrix. Thus, random Gaussian measurements Φ are universal to generate $\Theta = \Phi\Psi$ which has the RIP with a high probability [79].

3.2.2. Reconstruction Algorithm

CS theory provides the guarantee that a compressible signal can be in $\mathbb{R}^N$ and fully described by only *M* random measurements. Consequently, we can recover the original signal *D* from the compressed signal with only *M* random measurements. Since $M \ll N$, there are many $S^{'}$ that satisfy $\Theta S^{'} = \mathbb{C}$; they all lie on the (*N*-*M*)-dimensional hyperplane $H : N(\Theta) + S$ in $\mathbb{R}^N$ corresponding to the null space $N(\Theta)$ of Θ translated to the true sparse solution *S* because if $\Theta S^{'} = \mathbb{C}$ then $\Theta(\mathrm{S}^{'} + r) = \mathbb{C}$ for any vector *r* in the null space [80]. 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, random matrices Φ and Ψ to recover the original signal. 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 entries in S; hence a K-sparse vector has ℓ_0 norm K. Minimum ℓ_0 and ℓ_2 are not convenient to recover the original signal from the compressed signal, but we can exactly reconstruct the original signal by ℓ_1 norm with high probability and enough accuracy. Figure 3.8 compares ℓ_2 and ℓ_1 norms [81]. Figure 3.8- a shows a sparse vector s lies on a K-dimensional hyperplane aligned with the coordinate axes in $\mathbb{R}^N$ and also close to the axes. Figure 3.8-b shows that compressed sensing recovery via ℓ_2 minimization does not find the correct sparse solution s on the translated null space. Figure 3.8-c shows recovery via ℓ_1 norm with enough accuracy to find the correct sparse solution S.

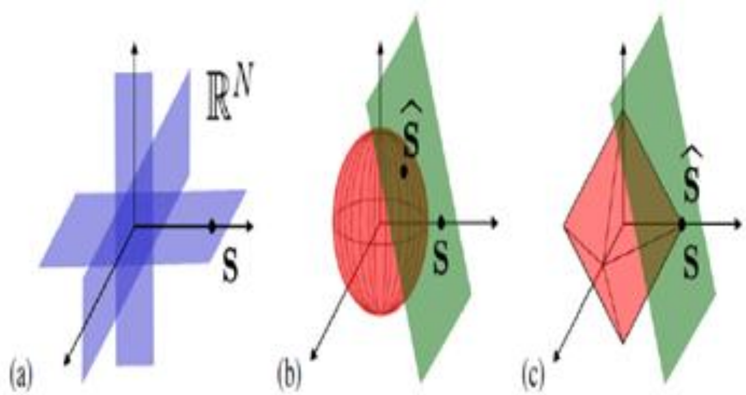


Fig.3.8-a,b, and c: Recover the original signal via ℓ_2 and ℓ_1 [81]

Figure 3.9 shows reconstruction procedure.

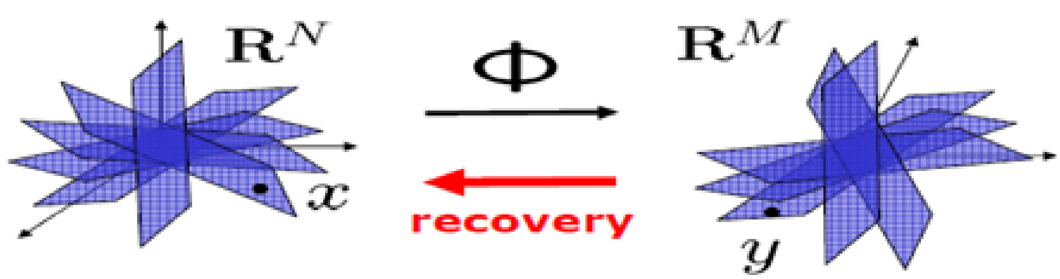


Fig.3.9: Reconstruction procedure

The CS theory surprises that from M iid Gaussian random measurements we can exactly reconstruct the original signal D with high probability via ℓ_1 optimization like [82]:

$$S = \arg\min \left\| S' \right\|_1 \quad \text{such that } \Theta S' = \mathbb{C} \tag{3.11}$$

which Θ is given by the following equation:

$$[\Theta]_{M\times N} = [\Phi]_{M\times N}[\Psi]_{N\times N} \tag{3.12}$$

Clearly, the reconstruction approach consists of the following steps:

►Take *M* random measurements.

►Select $[\Phi]_{M\times N}$ matrix of random measurements.

►Use $[\Psi]_{N\times N}$ sparsity basis matrix.

►Regenerate the length-*N* and original signal *D.*

3.3. Compressed Sensing in WBANs

The CS theory, as an emerging data compression methodology, permits catering for some important constraints in WBANs. Medical applications of WBANs based on CS theory cover continuous waveform sampling of biomedical signals, monitoring of vital signal information, and low rate power remote control of medical devices. The CS theory says many natural signals, such as biomedical ones, are sparse or near sparse in the sense that they have concise representations when expressed in the convenient basis. The CS scenario enables continuous waveform sampling data acquisition and compression that are suited for a variety of biomedical signals. The CS procedure that is presented in this thesis addresses both the energy and telemetry bandwidth constraints of WBANs. The CS theory states sparse or compressible signals such as some biomedical signals can be well recovered when minimizing ℓ_1 norm optimization, while satisfying the RIP condition for the random measurement matrix Φ and orthogonal basis Ψ. To verify this condition, it exploits a conventional Fast Fourier Transformation (FFT) to check signal sparsity. These signals have *K* non-zero coefficients and (*N*-*K*) zero coefficients with $K \ll N$ and can be well recovered using *M* projections or measurements such that $K \leq M << N$. As a result, the number of non-zero coefficients is small; the CS theory can, therefore, be applied to reduce the load of sampling. The biomedical signal D can be expressed as:

$$D = \sum_{i=1}^{N} S_i \Psi_i \tag{3.13}$$

where S is coefficient vector for D under the basis $\Psi = [\Psi_1, \Psi_2, \cdots, \Psi_N]$. If D has the most compact representation in Ψ, then D should be compressed if acquired in the proper basis. The CS theory also proposes that rather than acquire the entire signal and then compress, it should be possible to initially capture only the signal's useful information. In the CS theory, we have a $M \times N$ measurement matrix Φ and biomedical signal D with N-dimensional with $M \ll N$; then the compressed signal $\mathbb{C}$ can be expressed as:

$$[\mathbb{C}]_{M\times 1} = [\Phi]_{M\times N}[D]_{N\times 1} \tag{3.14}$$

In the reconstruction algorithm a practical approach is used to recover the original signal by solving the following convex optimization problem:

$$\text{minimize} \left\| D \right\|_1 \text{ subject to } \mathbb{C} = \Phi D \tag{3.15}$$

The recovered signal is then $D = \Psi C^*$ where C^* is the optimal solution. The ℓ_1-norm drives small coefficients to zero and needs only a small set of measurements M with $M \ll N$ to recover the original signal with N dimensions. The success of CS relies on incoherence between the matrices Φ and Ψ. The less coherence between Φ and Ψ means the fewer measurements M are needed to recover the original signal. Figure 3.10 illustrates CS theory in WBANs.

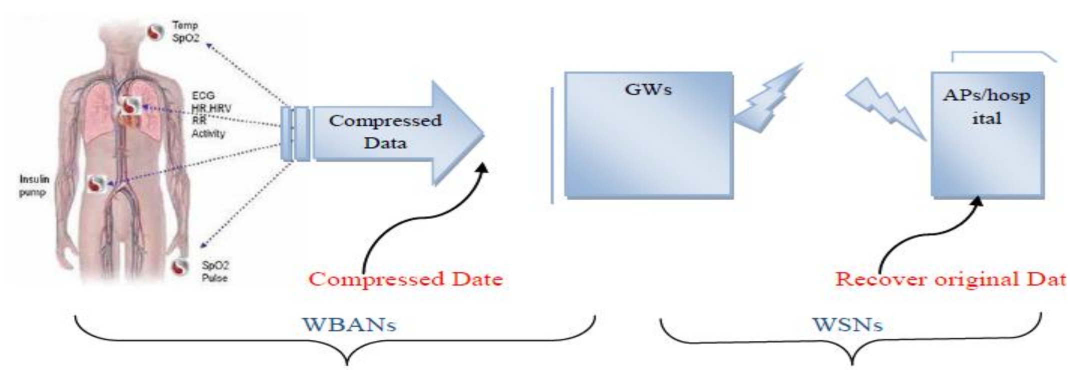


Fig.3.10: CS procedure in WBANs

As shown, the biomedical signals are compressed by wireless sensors. The collected compressed biomedical data are then transmitted wirelessly to Access Points (APs) at the hospital, ambulance, and helicopter. The APs are recovered compressed biomedical data for diagnostic and therapeutic purposes. Furthermore, the *D* data vector in WBANs is a sparse vector, because the GW needs to collect only *M* bits instead of *N* bits of data *(M≈K– sparse*) through the network. In the WBANs with *N* wireless sensor, sensor i is acquiring a sample d_i of the human body. The final goal in WBANs for medical applications is to collect data vector *D* of *N* wireless sensors in a suitable basis $\Psi = [\Psi_1][\Psi_2]\ldots[\Psi_N]$ like:

$$D = \sum_{i=1}^{N} d_i \Psi_i \tag{3.16}$$

In the *non-CS* scenario a node is receiving *N-1* packets and sends out *N* packets ((*N-1*) received packets plus its data), with each packet corresponding to the data sample from a wireless node. In WBANs with CS theory the GW needs to receive only *M (M≈K-sparse)* packets. In order to use CS, each node needs to know the value of Compress Ratio (*CR=N/K*) that is constant as well as the value of *N* [79]. The node i is computed *K=N/CR* and generates *K* values Φ_{ji} ($1 \le j \le k$) and creates a vector $D_i[\Phi_{1i}, \Phi_{2i}, \cdots \Phi_{ki}]$ 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* that correspond to the aggregated column vectors. Now the difference between CS and non-CS operation becomes clear: CS operation requires each node to send exactly *M* packets irrespective of what it has received; each node needs to know *CR* and *N* and then computes the value of (*M≈K*). The received vector in GW can be written as:

$$[\mathbb{C}]_{M\times 1} = [\Phi]_{M\times N}[D]_{N\times 1}\,. \tag{3.17}$$

Consequently, the received vector in GW is a condensed representation of the sparse events and can be expressed as:

$$\begin{pmatrix} \mathbb{C}_1 \\ \vdots \\ \mathbb{C}_M \end{pmatrix} = \begin{pmatrix} \Phi_{11} & \cdots & \Phi_{1N} \\ \vdots & \vdots & \vdots \\ \Phi_{M1} & \cdots & \Phi_{MN} \end{pmatrix} \begin{pmatrix} D_1 \\ \vdots \\ D_N \end{pmatrix} \quad . \tag{3.18}$$

Further, our simulation results show that by employing the CS the WBANs can achieve a higher transmission, a lower time delay, and a higher probability of success of data transmission than non-CS networks. Therefore, an application of CS theory to WBANs is an optimal solution for achieving robust WBAN with low sampling rate and reduced power consumption. The CS theory is essential for such a biomedical network by compressing; the data size is reduced, and fewer bandwidths are required to transmit data. Therefore, less power is required to process data. The discovering of these useful features improves understanding of the data, reduces computational storages and processing requirements and can increase prediction accuracy. We focus on feature extraction and feature evaluation with the aim to reduce the dimensionality of the biomedical data. Regarding suitability, CS theory holds promising improvements to these limitations through the following tasks:

► Compressed biomedical data in wireless nodes.

► Recover original data at GW.

Power consumption depends on the supply current and frequency. Reducing the current by applying a low sampling-rate procedure such as CS theory is a very effective way to reduce power consumption. The battery lifetime is related to the discharge rate or amount of current drawn. With CS, the number of bits of information decreases and the current drawn into the power supply is dropped. Moreover, the lifetime of power supply can be increased by drastically reducing the current from other units of biomedical nodes or often placing it in sleep mode, because the lifetime of power supply is related to the amount of its current drawn. The lifetime of the power supply in each biomedical node can be extended by drastically decreasing the amount of the current. Thus, each biomedical node can be designed to manage its local power supply by CS theory to maximize the lifetime. An important key for any biomedical node is to minimize power consumption in order to maximize the lifetime of network. By applying the CS theory, it possible to do the following; send biomedical data through the communication unit only when is required, increase the sleep time, and reduce the power required to process and communicate data. Therefore, changing between sleep and active modes is a good way to minimize power consumption. By reducing the sampling rate with the CS theory in each biomedical node, the sleep time is increased and consequently, the power consumption is reduced. As a result, if the number of bits of biomedical data is decreased, the transmission power and the transmission rate is increased; hence, power dissipation is decreased. The battery lifetime is related to the discharge rate or amount of current drawn. In order to design a robust biomedical network, the ideal biomedical node is designed with CS theory to consume little power, be capable of rapid data acquisition, be reliable and accurate for the long-term, and require no real maintenance.

3.4. Validation of CS to WBANs/WSNs

The CS theory is a revolutionary idea proposed recently to achieve a much lower sampling rate for sparse signals. Over the past few years, a new sampling theory of CS has begun to emerge, in which the sparse signal can recover the whole of the signal from a few random linear measurements instead from huge samples. In order to apply CS theory to WBANs and WSNs, we should verify two important conditions. First, we need to confirm that data vectors in WBANs/WSNs are sparse vectors and consequently, that CS theory can be employed in WBANs/WSNs. In the second condition, we need to prove the application of CS theory in layers of the WBANs/WSNs.

3.4.1. Two Important Questions

The first question is that, whether or not the information of *K-Sparse* of biomedical signals is damaged by the dimensional reduction from N to M bits of information. Surprisingly, the information is not damaged because of the D vector of biomedical signals is the sparse vector. If D is not sparse enough or if $M \leq N$, the signal is damaged since there are fewer equations than unknowns. The next question is how to develop a reconstruction algorithm to recover the data vector from the compressed data vector $\mathbb{C}$ under certain conditions and high probability [84]. We can recover the original signal D, by solving a convex optimization via ℓ_1 norm.

3.4.2. The Criteria of Sparsity

As a result, the CS theory can be employed in WBANs/WSNs if we can verify that the D data vectors are sparse. In this part, we want to investigate how to employ the CS theory in WBANs/WSNs, which mostly involve data of either a large number of wireless sensors or a large number of zero coefficients in sparse biomedical signals or zero non-overlap blocks in non-sparse signals. Typically, in WBANs/WSNs we have the following properties:

►There is a total of N sources randomly located in a field for WSNs and N samples for biomedical signals in WBANs.

►We denote K as the number of sparse.

►K is a random number and is much smaller than N.

►We denote $[D]_{N\times 1}$ as the event vector.

►Each component of $[D]_{N\times 1}$ has a random value.

►Obviously $[D]_{N\times 1}$ is a sparse vector since $K \le N$.

►There are M active monitoring BWSs trying to capture K events.

►The number of events K, the number of BWSs M, and total of sources N, have the following relation:

$$K \le M \ll N \quad . \tag{3.19}$$

Also in WBANs/WSNs we have:

►Very limited number of sparse biomedical signals in WBANs or very limited active sensors compared with the total of sensors in WSNs.

►Very limited number of events compared to the number of sources.

►Thus, the events are relatively sparse compared to the number of sources.

Figure 3.11 shows our model and emphasizes that compressed data is generated either by a GW in WBANs or a Base Station (BS) in WSNs using M random linear measurements. Hence, the compressed data can be generated from only M bits of information instead of N bits of information such as $M \approx K << N$, where K is the number of sparse. Regarding the explanation above, we can apply the CS theory to WBANs/WSNs as a low sampling method to reduce sampling rate and power consumption.

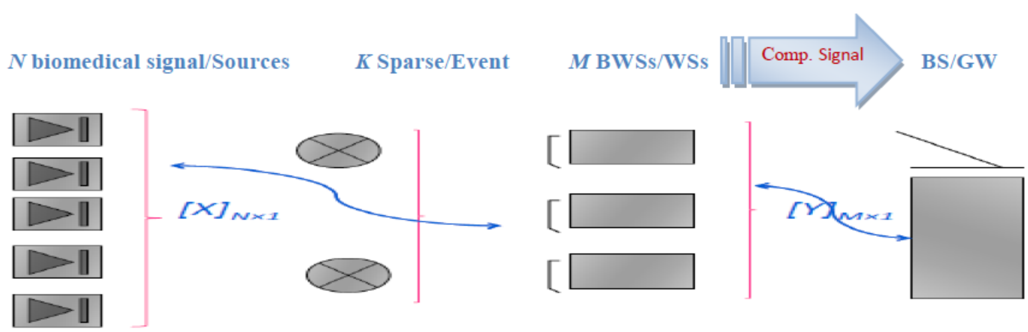


Fig.3.11: Model for WBANs/WSNs based on CS theory

Therefore, we can say data vectors in WBANs/WSNs are sparse vectors and consequently, CS theory can be employed in them. In a WBAN/WSN with N sources, each node acquires a sample D_i. The final goal is to collect data vector $D = [D_1, D_2, \cdots D_N]$ which has an M-Sparse in a proper basis as follows:

$$\Psi = [\Psi_1, \Psi_2, \cdots \Psi_N] \ . \tag{3.20}$$

CS suggests that, under certain conditions, instead of collecting D we can collect compressed vector $\mathbb{C} = \Phi D$, where Φ has $M \times N$ dimension with *i.i.d* random variables. Figure 3.12 shows operation of each node in non-CS and CS scenarios.

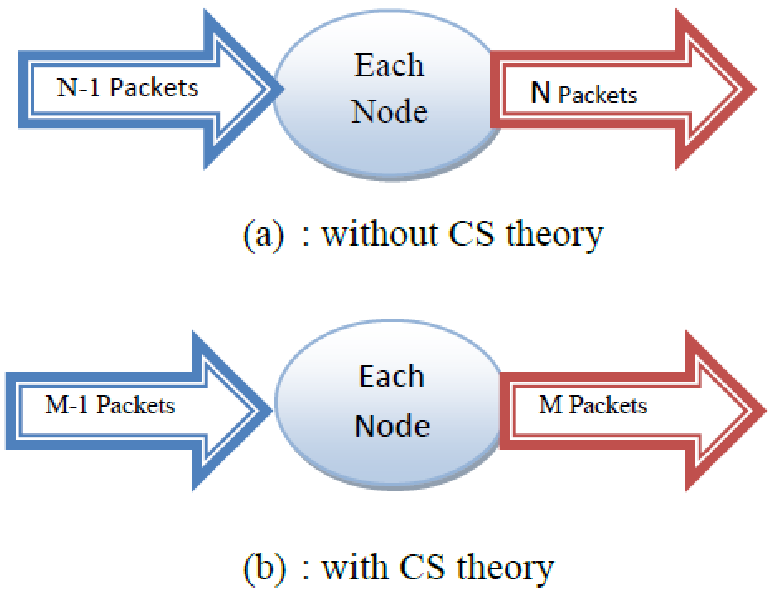


Fig.3.12: Operation of each node in non-CS and CS scenarios

In non-CS WBAN/WSN a node is receiving *N-1* packets and sends out *N* packets *(N-1)* received packets plus its data, with each packet corresponding to the data sample from a node, and the BS/GW needs to receive all *N* samples. In WBANs/WSNs with CS theory, the BS/GW needs only to receive *M (M≈K)* packets. The received vector in BS/GW can be written as [87]:

$$[\mathbb{C}]_{M\times 1} = [\Phi]_{M\times N}[D]_{N\times 1} . \tag{3.21}$$

3.4.3. Second Criteria

In WBANs/WSNs with *N* BWSs, all the BWSs read the information around in their monitoring distances except the BS or GW that only gather the data and make decisions. The job of the BWSs/WNs in the first layer is to collect the original data and transmit them to the other BWSs/WNs in the upper layer or second layer. The BWSs/WNs in the second layer not only gather the information of the first layer, but also implement the goal of data gathering with their own BWSs/WNs. By focusing on the small number of random measurements, the wireless nodes can reduce the correlation between the first layer and other layers to eliminate redundancy and thereby elevate the transmission rate. Figure 3.13 shows the basic model for WBANs/WSNs, which consist of four layers. The BWSs/WNs in layer four are called sink nodes or BS/GW.

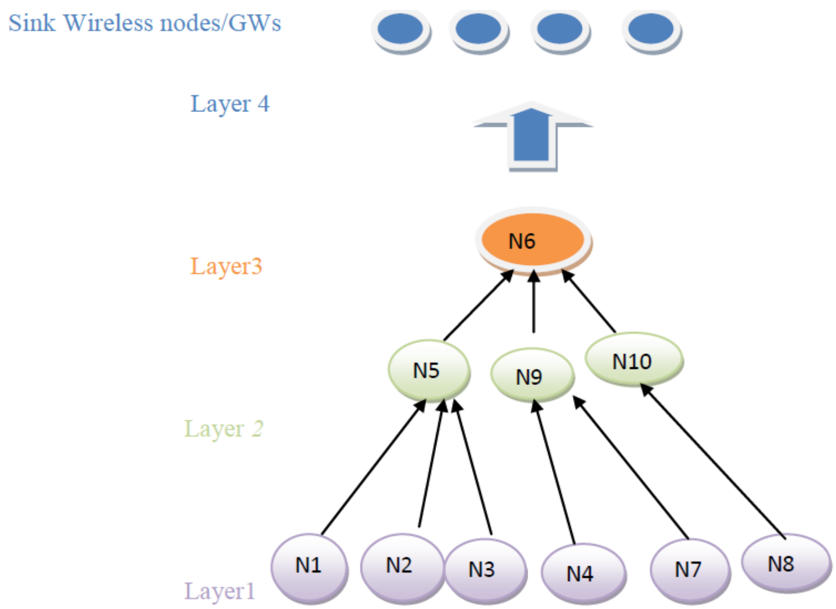


Fig.3.13: The structure of layers

Regarding the results of the last part, the BWSs/WNs have the Φ basis to decrease the amount of data. We take a sub-tree of the networks, including the BWSs/WNs $N_{1, 2, 3, 4, 5, 6}$ in Figure 3.14. The data of $N_{1, 2, 3, 4}$ and $D_{1, 2, 3, 4}$ are transmitted immediately by using their random basis vector, and generate the result $\Phi_{i1}D_1, \Phi_{i2}D_2, \Phi_{i3}D_3, \Phi_{i4}D_4$.

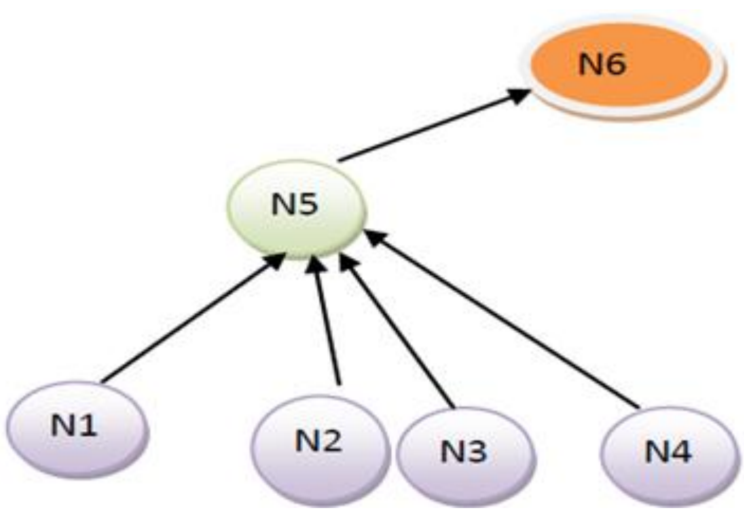


Fig.3.14: The sub-tree

In the second layer, node 5 collects the information and adds its own information as follows:

$$\mathbb{C}_i = \sum_{j=1,2,3,4,5} \Phi_{i\,1} D_j \quad . \tag{3.22}$$

The resulting data is sent to the router wireless node N_6 . Finally, the BWSs/WNs in sink/GW collect the compressed data. The formula for compressed data is:

$$\mathbb{C}_i = \sum_{j=1}^{N} \Phi_{i\,j} D_j \quad . \tag{3.23}$$

Eq. (3.22) can be re-written as:

$$\mathbb{C}_i = \left(\Phi_{i1}, \Phi_{i2}, \cdots \Phi_{iN}\right) \begin{pmatrix} D_1 \\ D_2 \\ D_3 \\ \vdots \\ D_N \end{pmatrix} \quad . \tag{3.24}$$

Thus, we have:

$$\begin{pmatrix} \mathbb{C}_1 \\ \mathbb{C}_2 \\ \vdots \\ \mathbb{C}_N \end{pmatrix} = \begin{pmatrix} \Phi_{11} & \Phi_{12} & \cdots & \Phi_{1N} \\ \Phi_{21} & \Phi_{22} & \cdots & \Phi_{2N} \\ \vdots & \vdots & \vdots & \vdots \\ \Phi_{M1} & \Phi_{M2} & \cdots & \Phi_{MN} \end{pmatrix} \begin{pmatrix} D_1 \\ D_2 \\ \vdots \\ D_N \end{pmatrix} \quad . \tag{3.25}$$

Therefore, the compressed data can be generated from only M bits of information instead of N bits of information, such as $M \approx K \ll N$ where, K is the number of the events or sparse in the WBANs/WSNs.

3.5. Structure of WBANs with CS theory

In a WBAN the BWSs collect, process, and communicate the important data wirelessly. The Personal Device (PD) such as the base station in WSNs gathers all the data acquired by the wireless nodes and informs the user (i.e. the patient, a nurse or medical center). Thus, power consumption can be divided into three units: sensing, communication, and data processing. The power available in wireless nodes is often restricted. This makes power optimization more complicated in WBANs to determine the lifetime of wireless nodes, especially in implanted sensors.

The lifetime of wireless nodes in WBANs for a given battery capacity can be enhanced by minimizing power consumption during the operation of the sensing, communication, and processing units. This is because power consumption is the most important factor to extend the WBAN's lifetime in EH systems. Therefore, application of the CS theory to WBANs provides the optimal solution for achieving robust WBAN with low-power technology. Furthermore, in most cases, a WBAN will be set up in the hospital by medical staff; consequently, it should be capable of reconfiguring itself later. By employing the CS theory as a new sampling method in WBANs, a network is designed to be self-organizing and self-maintained. Based on the suitability of WBANs with CS theory, our block diagram is shown in Figure 3.15.

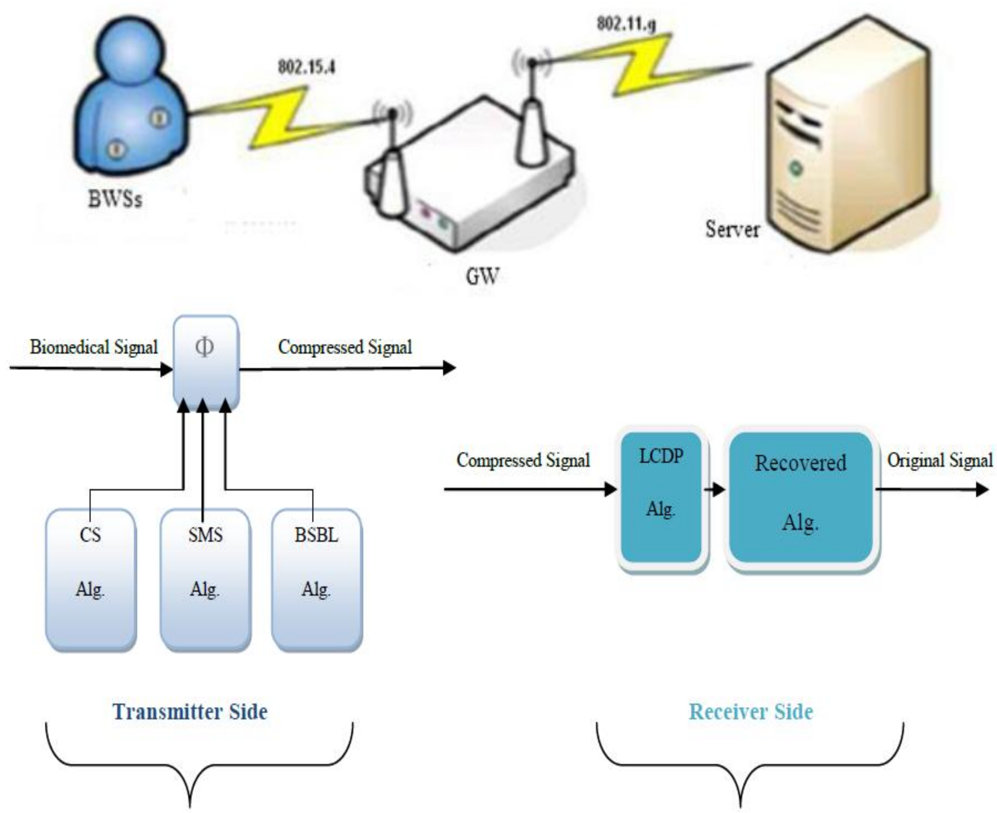


Fig.3.15:WBANs with CS theory at Transmitter/Receiver

In order to fully exploit the benefit of this block diagram, the following steps are first applied to biomedical signals at the BWSs:

Step1: Select biomedical signal.

Step2: Check the performance of CS.

Step3: If CS is not effective, employ BSBL framework.

Step4: Apply SMS algorithm for selecting random sensing matrix.

Step5: Generate the compressed signals.

Step6: Check the performance of compressed signal.

The block diagram at the receiver side (either GWs or APs) consists of the following steps:

Step1: Receive compressed signal at GWs or APs.

Step2: Apply LCDP algorithm for accurately detecting the compressed signals at the receiver side in the hospitals or medical centers.

Step3: Employ reconstruction approach by ℓ_1.

Step4: Apply a new reconstruction algorithm if needed.

Step5: Check the performance of the reconstruction algorithm.

Step6: Provide the original biomedical signal in the hospital or medical centers.

A frequency-hopping multiple access method is employed to combat interference and fading. At the receiver side, CS theory offers a reconstruction method to recover the original data from the compressed data under certain conditions with enough accuracy and high detection probability.

3.5. Chapter Summary

The emerging application of CS theory in medical areas has good potential to establish wireless healthcare systems. In this chapter, the CS theory as a new and low sampling theory is discussed. This theory states that a small number of random linear measurements of sparse signals contain enough information to collect, process, transmit, and recover the original signal. The signal representing sparsity in any orthogonal basis can be well reconstructed using ℓ_1 norm minimization, while satisfying the RIP condition for random measurement matrix Φ. The matrix is possible because of compressed sensing theory and the orthogonal Ψ in any domain. This chapter discussed a revolutionary idea proposed recently, CS theory, by which the sparse or compressive input signal is sampled and simultaneously compressed. This chapter also confirmed that CS theory by reducing the number of bits of information, reduced data size, required fewer bandwidths to transmit data, and required less power consumption to process data. This chapter also summarized that the compressed signal at the receiver side is a condensed representation of the sparse events and that it is possible to recover the original signal by only a small number of random linear measurements and compressed signal. Finally, this chapter emphasized that by applying CS theory in wireless medical body area networks, we are able to design a robust wireless medical body area network that provides remote patient monitoring systems, intelligent emergency care management systems, and ubiquitous mobile healthcare applications. The ideal wireless medical body area network should consume little power, be capable of rapid data acquisition, be reliable and accurate for the long-term, and require no real maintenance.

3.6. Plan for Next Chapter

In the next Chapter, we apply CS theory to WBANs with a single biomedical signal. Further, we select ECG signals as an example in order to explore the benefits of CS theory in WBANs with only one biomedical signal. The reason that we chose the ECG signal is due to its unique behavior. ECG signals generally show redundancy between adjacent heartbeats due to their pattern of sparsity in normal cases. This redundancy implies a high degree of common support between consecutive heartbeats. Long-term records of ECG signals have commonly been used to demonstrate important information from the heart for diagnostic and therapeutic purposes. That is why the quantity of data grows significantly and compression is required for reducing the storage and transmission times. Therefore, it is desirable to reduce the number of acquired ECG samples by taking advantages of the sparsity either in the number of non-zero samples or the non-zero blocks. Figure 3.16 shows the plan for next Chapter. As depicted in Fig.3.16, the following novelties are presented:

► Present a contribution from BSBL framework with CS theory for sparse and non-sparse ECG signals. The fundamental objective of this contribution is to apply CS theory for any ECG signal, including sparse and non-sparse signals.

►Present reconstruction algorithm for recovering compressed ECG signals based on an important contribution from BSBL framework and ℓ_1 norm on the receiver side of wireless networks. The main purpose of this algorithm is to recover non-sparse signals with or without a block structure.

►Apply SMS algorithm at the transmitter side of WBANs to select the best fit for random sensing matrix to compress ECG signals. The main objective of this algorithm is to confirm that a random sensing matrix is a suitable candidate matrix to recover the original signal from the compressed signal.

► Employ a detection algorithm for capturing the compressed received signals at the receiver side of WBANs. The fundamental objective of this algorithm is to increase the detection probability in receiving compressed ECG signals through computers at the hospital and medical centers for treatment and diagnostic purposes.

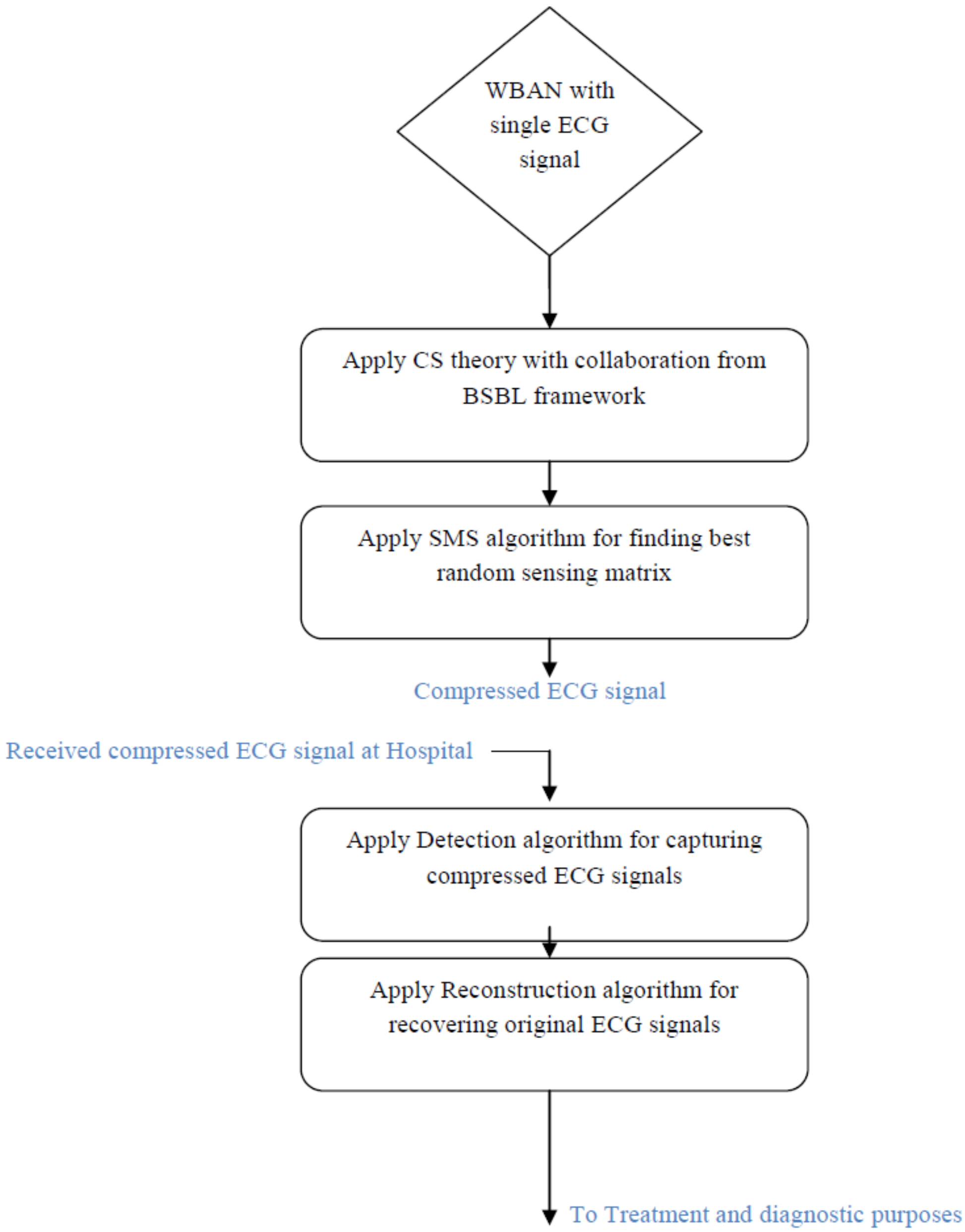


Fig.3.16: Plan for next chapter

Chapter 4

WBANs with Single Biomedical Signal Based on CS Theory

4.1. Motivation

The fundamental goal of this chapter is to apply the new SMS, Advanced BSBL, and LCDP algorithms based on CS theory to WBANs with a single biomedical signal in order to provide a robust wireless healthcare network. The ECG signal is selected as a sample of biomedical signals. The reason for selecting ECG signal as a sample is that ECG signals generally show redundancy between adjacent heartbeats due to their structure. This redundancy implies a high degree of common support between consecutive heartbeats. Long-term records of ECG signals have been commonly used to detect information from the heart diseases. That is why the quantity of data grows significantly, and compression is required for reducing the storage and transmission times. Hence, it is desirable to reduce the number of acquired ECG samples by taking advantage of the sparsity either in the number of non-zero samples or non-zero blocks. The assumption for this chapter is the use of one wireless ECG sensor for collecting ECG signals. This network is called wireless ECG system. Wireless ECG systems are responsible to wirelessly collect and transmit the vital signals of cardiac patients to medical centers for diagnostic and therapeutic purposes [83]. ECG is a noninvasive technique widely used in health care systems for diagnosis of heart diseases. However, the use of the conventional ECG system is restricted by patient's mobility, the system's transmission capacity, and physical size [84]. The aforementioned highlights the need and advantage of wireless ECG systems with low sampling-rate and low power consumption. There is a critical need to develop wireless ECG systems in order to achieve extended patient mobility. The other motivation of this chapter is to provide wireless ECG systems with a high detection rate, low sampling-rate, and an accurate reconstruction procedure. Figure 4.1 illustrates the plan for this Chapter.

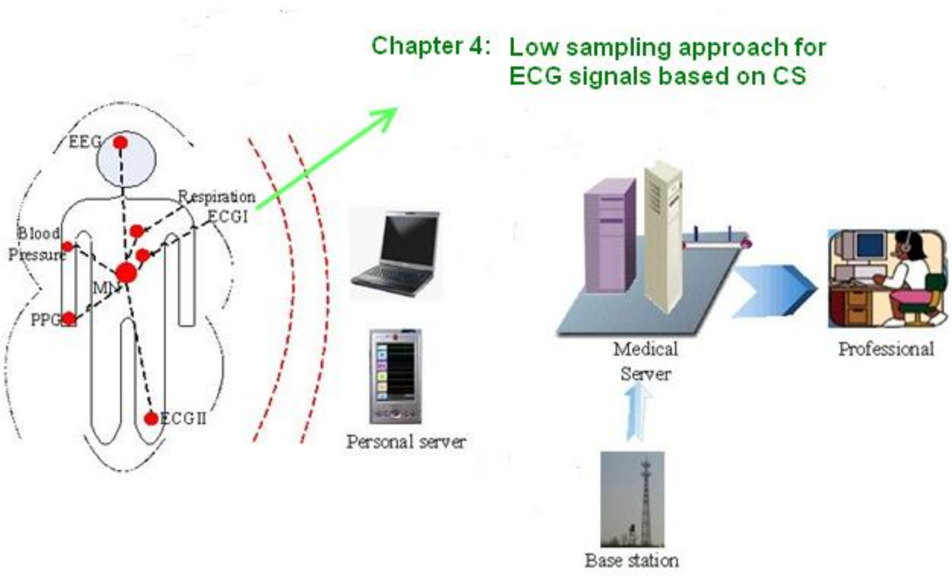


Fig.4.1: Plan for this chapter

This chapter is organized as follows: first, the fundamental contributions are described. Second, the proposed algorithms including reconstruction, SMS, and detection algorithms are applied to WBANs with single ECG signals. Third, simulation results, including results on *SNR* and *PRD* are presented. Fourth, the chapter summary and plan for next chapter are illustrated.

4.2. Contribution

The fundamental contribution of this chapter is to combine CS theory and BSBL framework to establish an advanced BSBL framework for compressing as well as recovering biomedical data, including sparse or non-sparse signals. The main objective of advanced BSBL framework is to recover non-sparse signals with or without a block structure. The main BSBL framework divides the non-sparse signal into non-overlapping blocks [85]. By employing this framework, a non-sparse signal can be partitioned into a concatenation of non-overlapping blocks of which only a few blocks are non-zero. The main structure of this framework is to explore and exploit the intra-block-correlation in terms of the entry values within each block [86]. The advanced BSBL framework with our new sub-algorithm is also able to recover non-sparse signals that have no specific block structure. This framework has a pruning mechanism and trims the blocks; therefore, if a non-sparse signal has no clear block structure, the advanced BSBL framework is still effective. In other words, the successes of CS theory rely on the key assumption that most entries of the biomedical signal must be zero, which means the biomedical signal must be a sparse signal. If this assumption does not hold, we should seek a new dictionary matrix, denoted by $D \in \mathbb{R}^{M\times N}$, so that the biomedical signal X can be expressed as:

$$[X]_{N\times 1} = [D]_{M\times N}[\mathrm{Z}]_{M\times 1}\ . \tag{4.1}$$

Where new signal Z is sparse signal and the compressed signal Y is obtained as:

$$[Y]_{M\times 1} = [\Phi]_{M\times N}[D]_{M\times N}[Z]_{M\times 1}\,. \tag{4.2}$$

See Figure 4.2 for a pictorial depiction of Eq. (4.2).

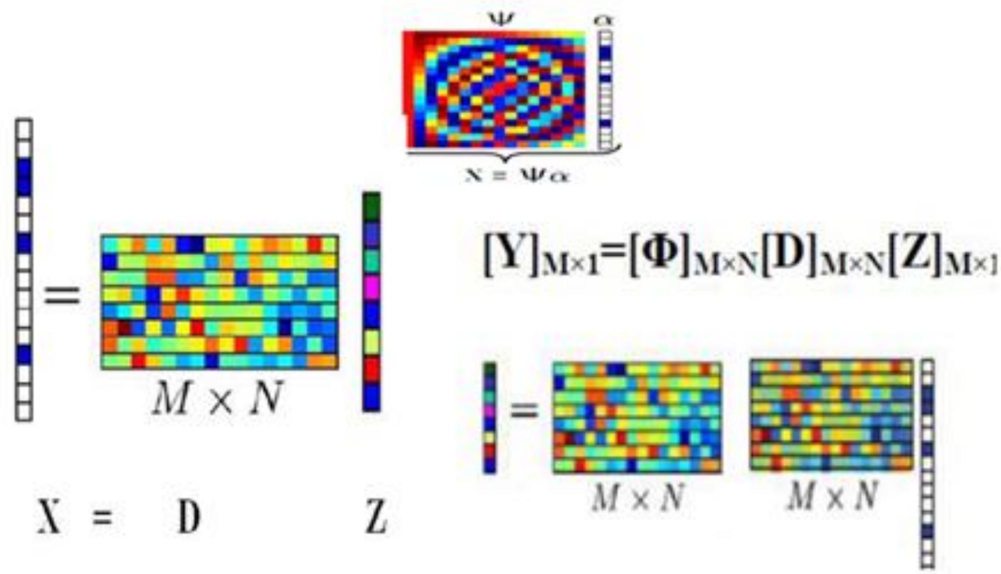


Fig.4.2: A pictorial depiction of Eq.(4.2)

If we are not able to define sparse signal Z, the advanced BSBL framework is employed to recognize a few non-zero and non-overlapping blocks into a biomedical signal. The successes of CS theory rely on the key assumption that most entries of the biomedical signal must be zero or that the biomedical signal must be a sparse signal. The main objective of advanced BSBL framework is to recover non-sparse signals with or without a block structure. The main BSBL framework divides the non-sparse signal into non-overlapping blocks. By employing this framework a non-sparse signal can be partitioned into a concatenation of non-overlapping blocks of which only a few blocks are non-zero. The main structure of this framework is to explore and exploit the intra-block-correlation in terms of entry values within each block. The advanced BSBL framework with our new sub-algorithm is also able to recover non-sparse signals that have no specific block structure. Figure 4.3 demonstrates our model for compressing any biomedical signal, whether sparse signal or non-sparse signal.

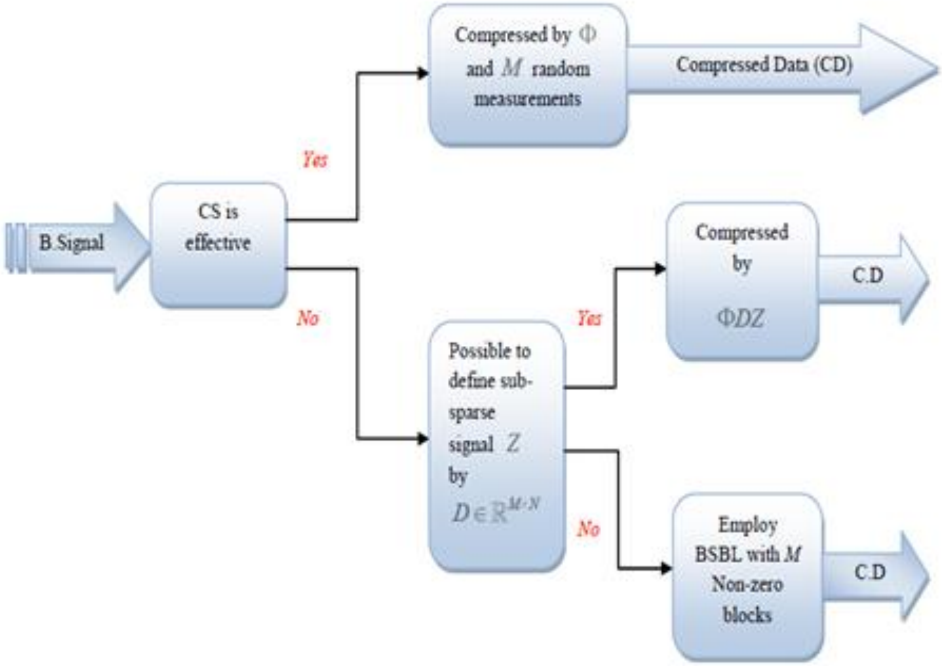


Fig.4.3: The proposed approach to compressed sparse or non-sparse biomedical signals

The proposed approach contains the following steps:

Step1: Consider a raw biomedical signal.

Step2: If CS is effective, generate the compressed signals. If not, go to Step 3.

Step3: If it is possible to recognize new dictionary D to define new sparse signal Z, go to step 4, otherwise go to Step5.

Step4: Generate compressed signal based on number of random measurements as:

$$[Y]_{M\times 1} = [\Phi]_{M\times N}[X]_{N\times 1}. \tag{4.3}$$

Step 5: Employ BSBL framework to provide a few non-zero blocks.

Step 6: Generate the compressed signals based on number of non-zero blocks.

In the second contribution, our new reconstruction algorithm based on the collaboration from BSBL framework and CS theory, is presented for recovering the original data. The main purpose of this algorithm is for recovering the compressed biomedical signals, including sparse and non-sparse signals at the medical centers with good level of accuracy. The proposed reconstruction algorithm has the following steps:

Step1: Generate: $\begin{cases} [\Theta]=[\Phi][\Psi] \\ Number\ of\ random\ measurements\ (M) \\ block\ distance\ d_0 \\ number\ of\ non-zero\ blocks(i)\ 0 \le i \le M \end{cases}$

Step2: Initialize $i=0$

Step3: $[\Theta]_0$ is constructed by selecting the columns of Θ in d_0

Step4: Find C_0 by solving $C_0 = \arg\min_C \|\mathbb{C}-\Theta_0 C\|_1^2$

Step5: Calculate: $\begin{cases} R_0 = \mathbb{C}-\Theta_0 C_0, CR_0 = R_0 / \mathbb{C}, \\ PRD_0 = \| R_0 \|_2 / \| \mathbb{C} \|_2 \end{cases}$

Step6: Solve the following equations:

$$\begin{cases} i = i+1 \\ C_i = \arg\min_C \|\mathbb{C}-\Theta_i C\|_1^2 \end{cases} . \quad (4.4)$$

Step7: Calculate: $R_i = \mathbb{C}-\Theta_i C_i, CR_i = R_i / \mathbb{C}, PRD_i = \| R_i \|_2 / \| \mathbb{C} \|_2$

Step8: Employ the learning rules.

Step8: Recover the original signal

In addition, in this Chapter, the SMS and detection algorithms are presented. The main purpose of the SMS algorithm is to find the best fit for random sensing matrix in CS theory in the sense that it ensures exact recovery of the original signal from the compressed signal at the receiver side. In CS, the random measurement matrix $[\Phi]$ is a key component for compressing the input signals [127]. Two key features are needed for the successful implementation of CS approach: sparsity of the biomedical signal and a high degree of incoherence between the sparsity basis $[\Psi]$ and random measurement matrix $[\Phi]$. Bernoulli Toeplitz, Gaussian Circulant, and Binary Toeplitz matrices are examined to find out the best fit for random sensing matrix. The selection algorithm for Φ consists of the following steps:

Step1: Consider raw biomedical data.

Step2: Apply DTA approach to raw data.

Step3: Select Initial Square Matrix.

Step4: Apply Row Selection Scheme (select the first *M* rows as the initial sensing matrix Φ).

Step5: Compare with Binary Toeplitz Matrix.

Step6: If Φ is Binary Toeplitz Matrix Stop, the Algorithm is completed.

Step7: If not, M=M+1 and go back to Step 4.

The next contribution of this thesis is to establish a new detection algorithm for capturing the compressed ECG signals at the receiver side. The purpose of the detection algorithm is to detect the compressed signals at GWs or APs. The reliability of the wireless medical systems is particularly important to ensure that the receiver side is able to receive biomedical signals with high accuracy. In this contribution, we present a simple but highly reliable detection algorithm for wireless medical systems. The proposed detection algorithm consists of two stages: 1. Feature extraction, which includes digital filtering and linear transformation, and 2. Decision making stage to locate the biomedical signals. The digital filtering limits the filtering operation to just one time. The decision-making stage uses Adaptive Threshold Mechanism (ATM) approach in order to control the detection level. The threshold value depends on the features of the received biomedical signals, and it is updated periodically based on biomedical features. The Hamming Window (HM) approach for the feature extraction stage and the Peak Finding Schemes (PFS) procedure for the decision making stage are applied to simulate the highly reliable detection algorithm. The output signal of the filtering process with HM is bipolar. Therefore, the signal is rectified to prevent detection errors where a signal's polarity changes. By employing the Shannon Energy Transformation (SET) algorithm during the feature extraction stage, the energy values that are E_s smaller than the threshold are set to zero, and other energy values are retained. The detection algorithm for GWs or APs contains the following steps:

Step1:Receive biomedical signal at GW.

Step2:Apply Feature Extraction Stage, including digital filtering and energy transformation.

*Step3:*Employ Hamming tool and Shannon Energy transformation code in C++.

*Step 4:*Establish Decision Stage, including Peak Finding and Peak Clipping Schemes.

*Step5:*Employ Peak finding and Peak clipping codes in C++.

Step6:Detect biomedical features for medical purposes.

In Sections 4.3 through 4.5, we present our contributions with more details, and in Section 4.6 we apply the new algorithms to ECG signals.

4.3. Solution for Non-Sparse signal

The success of CS theory relies on the key assumption that most entries of the signal D are zero (i.e. D is sparse signal). If the input signal D is not sparse by its nature, the CS theory is ineffective to recover the original signal. Therefore, the CS theory needs to be augmented by collaborations from new solutions for non-sparse signals. The solutions for non-sparse signals can be divided into two options. The first option is to seek a new dictionary matrix such that the input signal can be changed to a new and sparse signal. The second option is to employ a BSBL framework for recovering non-sparse signals.

4.3.1. New Dictionary

The objective of this option is to seek a new dictionary $\Omega \in \mathbb{R}^{M\times N}$ such that a new sparse signal Z can be expressed as:

$$[D]_{N\times 1} = [\Omega]_{M\times N}[Z]_{M\times 1}\,. \tag{4.5}$$

The compressed signal $\mathbb{C}$ can be re-written as:

$$[\mathbb{C}] = [\Phi][\Omega][\mathrm{Z}]\,. \tag{4.6}$$

The reconstruction algorithm consists of the following steps:

►Recover Z using $\mathbb{C}(\Phi\Omega)^{-1}$

►Recover D using (ΩZ)

►Employ the following equation:

$$D = \arg\min \|D\|_1 \text{ subject to } \mathbb{C}{=}\Phi D, \tag{4.7}$$

where D represents the estimated value of the L_1 norm of D,and minimizing the L_1 norm in the Eq. (4.7). The main problem with this option is the big challenge of finding out an optimal dictionary. For this reason, we move to the second option, which is to apply the BSBL framework.

4.3.2. Advanced BSBL Framework

The main objective of the advanced BSBL framework is to recover non-sparse signals with or without a block structure. The BSBL framework divides the non-sparse signal into non-overlapping blocks [87]. By employing this framework, a non-sparse signal can be partitioned into a concatenation of non-overlapping blocks of which only a few blocks are non-zero [88]. The main structure of this framework is to explore and exploit the intra-block-correlation in terms of entry values within each block. The advanced BSBL framework with our new sub-algorithm is also able to recover non-sparse signals that have no specific block structure. Therefore, if a non-sparse signal has no clear block structure, the advanced BSBL framework is still effective. The advanced BSBL framework is capable of solving the following problems:

►Recover non-sparse signals with block partition structure

►Recover non-sparse signals without any block structure

The simulation results confirm this advanced BSBL framework has superior performance compared to the current procedures. Two sub-algorithms are presented to provide an advanced BSBL framework. In the first sub-algorithm, a priori knowledge of the block partition is required. The second sub-algorithm relies on a weak assumption about the block structure and actually can be used when there is no available information about block partition.

4.3.2.1. Sub-Algorithm I

In this sub-algorithm, the input signal D has a block structure. It is divided into a set of K non-overlapping blocks and can be expressed as follows [89]:

$$D = [d_1 \cdots d_n, \cdots, d_{n_{K-1}} \cdots d_{n_K}]. \tag{4.8}$$

where blocks can be expressed as[89]:

$$[d_1, \cdots, d_n] = D_1^T \text{ and } [d_{n_{K-1}}, \cdots d_{n_K}] = D_K^T. \tag{4.9}$$

In K non-overlapping blocks only G blocks are non-zero such that $G \ll K$. The compressed signal is found as:

$$\mathbb{C} = \Phi D. \tag{4.10}$$

Here $\mathbb{C} \in \mathbb{R}^{G \times 1}$, $\Phi \in \mathbb{R}^{G \times N}$,and $D \in \mathbb{R}^{N \times 1}$ are the compressed signal, random sensing matrix, and block sparse signal respectively. In this sub-algorithm, we assume each block $\boldsymbol{D_i} \in \mathbb{R}^{\boldsymbol{d_i} \times 1}$ has multivariate Gaussian distribution with parameters Υ_i and β_i and can be expressed as:

$$\begin{cases} P(D_i; \Upsilon_i, \beta_i) \sim N(0, \Upsilon_i \beta_i) \\ \qquad i = 1, \cdots K \end{cases}, \tag{4.11}$$

where Υ_i controls the block-sparsity of the input signal and has a non-negative value. In the learning procedure, most Υ_i tend to be zero which prompts the idea of sparsity at the block levels. In Eq. (4.11), $\beta_i \in \mathbb{R}^{d_i \times d_i}$ captures the intra-correlation structure of the i^{th} block and is a positive definite matrix. By assuming that the K blocks are mutually uncorrelated to each other, the prior of the input signal is found as:

$$P(D; \{\Upsilon_i, \beta_i\}_{i=1}^K) \sim N(0, \sum\nolimits_0), \tag{4.12}$$

Where Σ_0 is a block-diagonal matrix with each principal block given by $\Upsilon_K \beta_K$ and can be expressed as follows [90]:

$$\sum\nolimits_0 = diag(\Upsilon_1 \beta_1, \cdots, \Upsilon_K \beta_K)\,. \tag{4.13}$$

By using Maximum-A-Posteriori (MAP) approach, the posterior of the original signal D can be directly obtained by estimating the following equation:

$$\begin{cases} P(D / \mathbb{C}; \{\Upsilon_i, \beta_i\}_{i=1}^{K}) = N(\mu_D, \sum\nolimits_D) \\ \mu_D = \sum\nolimits_0 \Phi^T (\Phi \sum\nolimits_0 \Phi^T)^{-1} \mathbb{C} \\ \sum\nolimits_D = (\sum\nolimits_0^{-1} + 1/\lambda(\Phi^T \Phi))^{-1} \end{cases}, \tag{4.14}$$

where λ is a positive scalar. The signal D is learned and estimated by learning parameters $\{\Upsilon_i, \beta_i\}_{i=1}^{K}$, and the original signal D is directly obtained from the mean of posterior MAP approach. Thus, the fundamental objective is to learn the hyper-parameters Υ_i and β_i with intra-vector correlation. The interactive leaning procedure for Υ_i is shown in Table 4.1:

Table 4.1: The interactive learning procedure for Υ_i

$\sum_0 \Phi^T (\Phi \sum_0 \Phi^T)^{-1} \mathbb{C} \rightarrow \mu_D$
$\sum_0^{-1} + 1/\lambda(\Phi^T \Phi)^{-1} \rightarrow \sum D$
$(1/d_i) T_r [\beta_i^{-1} (\sum_D^i + \mu_D^i (\mu_D^i)^T) \rightarrow \Upsilon_i$

In Table 4.1, μ_D^i is the corresponding $i-th$ block in $\boldsymbol{\mu_D} \in \mathbb{R}^{\boldsymbol{d}_i \times 1}$ and Σ_D^i is defined as the corresponding $i-th$ principle diagonal block in $\sum_{\boldsymbol{D}} \in \mathbb{R}^{\boldsymbol{d}_i \times \boldsymbol{d}_i}$. The estimation of D is given by μ_D when the procedure is converged. To drive a learning rule for β_i the first-odder Auto-Regressive (AR) method is used. This method is a sufficient model for intra-block correlation. Based on this model, the Toeplitz matrix applies for hyper-parameter β_i. The learning rule for β_i can be expressed as:

$$(1/K) \sum_{0}^{K} \frac{\sum_D^i + \mu_D^i (\mu_D^i)^T}{\Upsilon_i} \rightarrow \beta_i\,. \tag{4.15}$$

In this learning rule, all blocks are constrained to have the same size and same correlation structure to prevent over fitting. The purpose is to find:

►A positive definite and symmetric matrix β_i

► β_i would be close to β_i with the elements along the main diagonal and sub-diagonal

Based on this method, a possible form from β_i is given by:

$$\beta_i = Toeplitz([1, \hat{r}, \cdots, \hat{r}^{d-1}]) . \tag{4.16}$$

where in the matrix form can be expressed as follows:

$$\beta_i = \begin{pmatrix} 1 & \hat{r} & \cdots & \hat{r}^{d-1} \\ \hat{r} & 1 & \cdots & \hat{r}^{d-2} \\ \vdots & \vdots & \vdots & \vdots \\ \hat{r}^{d-1} & \hat{r}^{d-2} & \cdots & 1 \end{pmatrix}, \tag{4.17}$$

where $\hat{r}$ can be expressed as:

$$\hat{r} \triangleq sign(\frac{m_1}{m_0}) \min\{\left|\frac{m_1}{m_0}\right|, 0.99\}, \tag{4.17}$$

where m_0 is the average of the elements along the main diagonal and m_1 is the average of the elements along the main sub-diagonal of matrix β_i and can be found as follows:

$$m_{0,1} = \sum_{i=1}^{K} m_{0,1}^{i} . \tag{4.18}$$

The learning rule for β_i consists of the following steps:

►Derive the learning rule for β_i

►Obtain $\hat{r}$ by averaging corresponding elements from all the matrices $\beta_i (\forall_i)$

►Obtain β_i for each block in Eq. (4.14)

►Select $\beta_i = \beta_i$

4.3.2.2. Sub-Algorithm II

The main objective of this sub-algorithm is to recover biomedical signals with no block partition. This sub-algorithm relies on two weak assumptions. The first assumption is about the size of non-zero blocks. Based on this assumption all the non-zero blocks are of equal size L and arbitrarily located. The second assumption is about the distribution of each block. Based on this assumption each block satisfies a multivariate Gaussian distribution with zero mean and covariance matrix given by $\Upsilon_i \beta_i$ where $\beta_i \in \mathbb{R}^{L \times L}$ [91]. The sub-algorithm consists to the following steps:

►Select the number of possible blocks as P in the original signal D as:

$$P \triangleq N - L + 1. \tag{4.19}$$

►The $i-th$ block starts at the $i-th$ element and ends at the $(i+L-1)-th$ element of the original signal D

►Select the prior value of D as the form:

$$P(D) \sim N(0, \sum\nolimits_0). \tag{4.20}$$

►Start estimating the hyper-parameters Υ_i, β_i

►Expand the covariance matrix as follows [92]:

$$\Sigma_0 = Bdiag(\Upsilon_1 \beta_1, \cdots, \Upsilon_P \beta_P) \in \mathbb{R}^{PL \times PL}, \tag{4.21}$$

where $Bdiag(.)$ denotes a block diagonal matrix with the principal diagonal block given by $\Upsilon_1 \beta_1, \cdots \Upsilon_P \beta_P$. Now it is clear that $\Upsilon_i \beta_i$ does not overlap with other $\Upsilon_j \beta_j (i \neq j)$.

►Use the decomposition equation as follows:

$$D = \sum_{i=1}^{P} E_i Z_i, \tag{4.22}$$

where E_i is a zero matrix except that the section from its $i-th$ row to $(i+P-1)-\text{th}$ row is replaced by the identify matrix I and can be expressed as follows:

$$\begin{cases} E\{Z_i\} = 0, \quad \mathrm{E}\{\mathrm{Z}_i Z_i^T\} = \delta_{i,j} \Upsilon_i \beta_i \\ \qquad \delta_{i,j} = 1 \text{ if } i = j \\ \qquad \delta_{i,j} = 0 \quad \text{O.W} \end{cases}. \tag{4.23}$$

and Z is obtained by:

$$Z \triangleq [Z_1^T, \cdots, Z_P^T] \sim N(0, \sum\nolimits_0). \tag{4.24}$$

►Expand the Eq. (4.10) as [93]:

$$\mathbb{C} = \sum_{i=1}^{P} \Phi E_i Z_i = HZ, \tag{4.25}$$

where H is defined as:

$$H \triangleq [\mathrm{h}_1, \cdots, \mathrm{h}_P], \tag{4.26}$$

and h is obtained by:

$$h_i = \Phi E_i \, . \tag{4.27}$$

►Employ the learning rule in the Table 4.2.

Table 4.2: Learning rule for β_i

$\Sigma_0 H^T (H\Sigma_0 H^T)^{-1}\mathbb{C} \to \mu_D$
$\Sigma_0 - \Sigma_0 H^T (H\Sigma_0 H^T)^{-1} H\Sigma_0 \to \Sigma_D$
$(1/\mathrm{P})\sum_{i=1}^{P} \frac{\sum_D^i + \mu_D^i(\mu_D^i)^T}{\Upsilon_i} \to \beta$
$\frac{T_r[\mathrm{H}^{-1}(\sum_D^i + \mu_D^i(\mu_D^i)^T]}{L} \to \Upsilon_i$

Here μ_D^i and Σ_D^i are the corresponding $i-th$ block in μ_D and main diagonal block in Σ_D respectively. In the learning rule Υ_i trimmed mean (T_r) is computed just as an ordinary mean except that a pre-specified percentage of the extremes is first omitted.

►Finally, after convergence, the original signal D is recovered by:

$$D = \sum_{i=1}^{P} E_i Z_i \, . \tag{4.28}$$

4.4. SMS Procedure

One of the fundamental purposes in CS theory is to determine whether a random sensing matrix is a suitable matrix to ensure recovery of the original signal from the compressed signal. The main equation in the CS theory is given by:

$$\mathbb{C} = \Phi D \quad \|D\|_0 \ll M, \tag{4.29}$$

where $\| \, . \, \|_0$ counts the number of non-zero entries, M is the number of random measurements, N is the total of entries with $M \ll N$, and $\Phi \in \mathbb{R}^{M\times N}$ is a random sensing matrix. The target is to recover original signal $D \in \mathbb{R}^N$ from a small number of its random measurements from $\mathbb{C} = \Phi D \in \mathbb{R}^{M\times 1}$, where Φ is a known random sensing matrix with entries drawn independently from specific probability distributions and with $M \ll N$ to establish exact recovery of the original signal D. The fundamental condition for this recovery is to satisfy RIP property by the random sensing matrix [93]. If the random sensing matrix satisfies this property of order $3M$, which means all values of all sub-matrices of random sensing matrix should lie in the interval

$\left(\sqrt{\frac{2}{3}}, \sqrt{\frac{4}{3}}\right)$, the method obtains the exact recovery of the original signal D. Therefore, the random sensing matrix Φ should satisfy the PRP property order $3M$ in the following sense:

► Φ_T with $T \subset \{1, 2, \cdots, N\}$ denotes a $M \times T$ sub-matrix obtained by retaining the columns of Φ corresponding to the indices in T.

► $\delta_{3M} \in (0, 1/3)$ is a constant.

► $\forall Z \in \mathbb{R}^T$, the random sensing sub-matrix Φ should satisfy the following equation for all of subset T with $|T| \leq 3M$.

$$(1-\delta_{3M})\|Z\|_2^2 \leq \|\Phi_T Z\|_2^2 \leq (1+\delta_{3M})\|Z\|_2^2 \tag{4.30}$$

►As a result, the original signal D can be exactly recovered by solving the following convex problem:

$$D = \arg(\min \|Z\|_1 \text{ subject to } \mathbb{C}=\Phi Z) \tag{4.31}$$

Further, we show the Binary Toeplitz matrix, whose elements have the i.i.d property, to illustrate superior performance compared to other random matrices.

4.4.1. Toeplitz Matrix

The Toeplitz random sensing matrix $\Phi \in \mathbb{R}^{M \times N}$ in the probability distribution $P(\Phi)$ can be expressed as follows [94]:

$$\begin{pmatrix} \Phi_N & \Phi_{N-1} & \cdots & \Phi_1 \\ \Phi_{N+1} & \Phi_N & \cdots & \Phi_2 \\ \vdots & \ddots & \vdots & \vdots \\ \Phi_{N+M-1} & \cdots & \Phi_{M+1} & \Phi_M \end{pmatrix} \tag{4.32}$$

where $\Phi_{i,j} = \Phi_{i+1,j+1}$ and the entries $\{\Phi_i\}_{i=1}^M$ have been drawn independently from specific distributions such as Binary or Bernoulli and have the following properties:

►They are Toeplitz matrices.

►They satisfy RIP property of order $3M$ for every $\delta_{3M} \in (0, 1/3)$, because if Eq. (4.30) holds for any T then it also holds for all $T' \subset T$.

►The Toeplitz sub-matrices satisfy Eq. (4.30) and are also sufficient to recover the original signal.

The $P(\Phi)$ shows a probability distribution that generates a $M \times N$ random sensing matrix for every $\delta_{3M} \in (0,1/3)$ and every $T \subset \{1,2,\cdots,N\}$ with $|T| = 3M$. The $M \times N$ random sensing matrix has at least the following probability [95]:

$$P(\Phi) = 1 - e^{-f(M,\delta_{3M})} \tag{4.33}$$

where $f(M,\delta_{3M})$ is a real-value function of M and δ_{3M} and can be found as:

$$f(M,\delta_{3M}) = 3M\ln(12/\delta_{3M}) - \ln(2) \tag{4.34}$$

The probability distribution $P(\Phi)$ can be expressed as [96]:

$$N(0,1/M) = \begin{cases} +\sqrt{\dfrac{1}{M}} \textit{with probablity} \dfrac{1}{2} \\ -\sqrt{\dfrac{1}{M}} \textit{with probability} \dfrac{1}{2} \end{cases} \tag{4.35}$$

and with RIP property can be expressed as:

$$N(0,1/M) = \begin{cases} +\sqrt{\dfrac{3}{M}} & \textit{with} \ \dfrac{1}{6} \\ 0 & \textit{with} \ \dfrac{2}{3} \\ -\sqrt{\dfrac{3}{M}} & \text{with} \ \dfrac{1}{6} \end{cases} \tag{4.36}$$

4.4.2. Gaussian Circulant Matrix

The Circulant matrix $[\Phi]_{M\times N}$ can be expressed as [97]:

$$\Phi = \begin{pmatrix} \Phi_N & \Phi_{N-1} & \cdots & \Phi_1 \\ \Phi_1 & \Phi_N & \cdots & \Phi_2 \\ \vdots & \ddots & \ddots & \vdots \\ \Phi_{M-1} & \cdots & \cdots & \Phi_N \end{pmatrix} \tag{4.37}$$

The Circulant matrix is specified by the vector A, which appears as the first column of Φ. The remaining columns and rows are obtained from cyclic permutations and reverse order of the vector A. The entries of Φ are drawn independently from the given distributions [98]. If Φ satisfies RIP property for every $\delta_{3M} \in (0,1/3)$ with at least the following probability, the original signal can be recovered from the compressed signal.

$$P(\Phi) = 1 - e^{CK/M^2} \tag{4.38}$$

Where C is constant and K is the number of non-zero entries. Further, we show that the Circulant matrix does not hold to the above condition.

4.4.3. Binary Toeplitz Matrix

As was mentioned, any sparse signal D can be expressed by transform domain Ψ that is as:

$$D = \Psi S \tag{4.39}$$

where $S \in \mathbb{R}^N$, $\Psi \in \mathbb{R}^{N\times N}$, and Ψ, Φ should satisfy RIP of order $3M$ for successful recovery of S with i.i.d random sensing matrix for Φ with an orthonormal base for Ψ. In random binary case, we have the following rules:

► Ψ can be expressed as:

$$\Psi = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ 1 & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 1 & \cdots & 1 & 1 \end{pmatrix} \tag{4.40}$$

► $\{\Phi_i\}_{i=1}^{N+M-1}$ be a sequence of random binary variables drawn independently.

► H is a $N \times N$ differencing operator as [99]:

$$\mathrm{H} = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ -1 & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ -1 & \cdots & -1 & 1 \end{pmatrix} \tag{4.41}$$

► Φ_L defines a cascade of Toeplitz matrix Φ and H as:

$$\Phi_L = \begin{pmatrix} \Phi_N - \Phi_{N-1} & \cdots & \Phi_2 - \Phi_1 & \Phi_1 \\ \Phi_{N+1} - \Phi_N & \cdots & \Phi_3 - \Phi_2 & \Phi_2 \\ \vdots & \cdots & \cdots & \vdots \\ \Phi_{N+M-1} - \Phi_{N+M-2} & \cdots & \Phi_{M+1} - \Phi_M & \Phi_M \end{pmatrix} \tag{4.42}$$

The matrix Φ_L has the following interesting properties:

• Φ_L has only $(N + M - 1)$ elements.

• Multiplication ΦH requires only $\mathrm{O}(N \log_2(N))$ operations [100].

• The product matrix $\Phi_L \Psi$ is a Toeplitz matrix and satisfies the RIP property.

The use of Binary Toeplitz matrices is a desirable alternative for a number of application areas such as biomedical signals. The Binary Toeplitz-structured matrices as the random sensing matrices in CS theory have the following important benefits:

►It requires generating only $O(N)$ independent random variables, while other random sensing matrices require generating $O(NM)$ independent random variables.

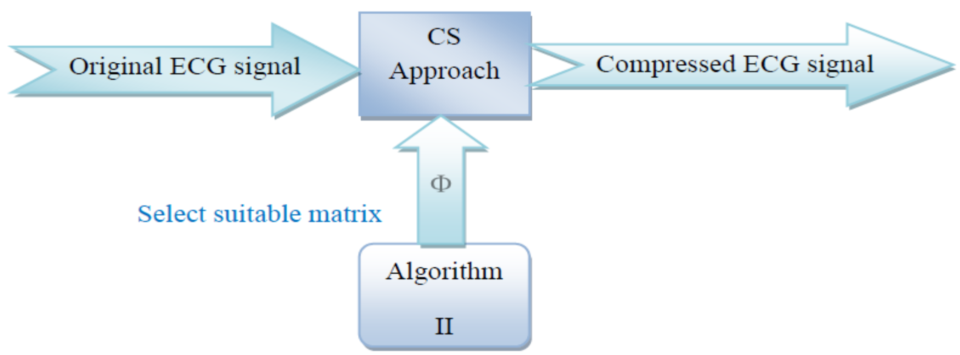
►Multiplication with a Binary Toeplitz matrix can be implemented using Fast Fourier Transform (FFT) and requires $O(N\log_2(N))$ operations, while multiplication of other random sensing matrices requires $O(MN)$ operations.

►They show faster acquisition and reconstruction process.

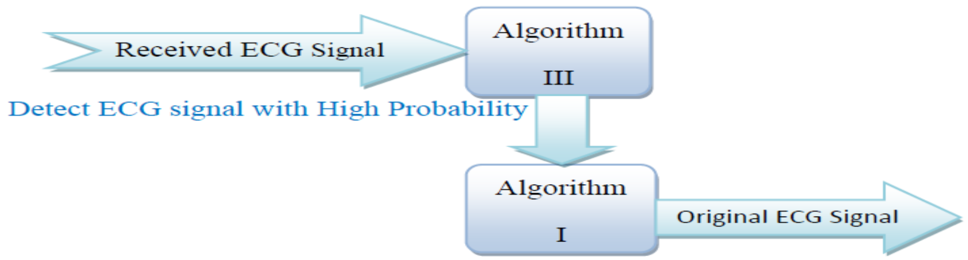
As a result, the Toeplitz matrices, whose random elements are drawn independently from binary distribution, show superior performance compared to most existing matrices.

4.5. Integration of Proposed Algorithms to Wireless ECG Systems

Figure 4.4 shows the combination of the reconstruction algorithm as algorithm I, SMS algorithm as algorithm II, Detection algorithm as algorithm III in the transmitter and receiver sides of wireless ECG systems.



(A): Wireless ECG Systems/Transmitter



(B): Wireless ECG Systems/Receiver

Fig.4.4: Combination of three algorithms

Fig. 4.4 demonstrates that SMS algorithm is employed at transmitter side to provide a compressed ECG signal that is sparse either in the number of non-zero samples or non-zero blocks. On the receiver side a reconstruction algorithm as well as a detection algorithm is applied to detect and recover the original ECG signal at either GWs or APs. In next section, the wireless ECG systems as a new cardiac monitor are introduced. Second, the fundamental steps for our algorithms are demonstrated. Third, the performance criterion to validate the simulation results is presented.

4.5.1. Wireless ECG systems

ECG signals are widely used in health care systems because they are noninvasive mechanisms to establish medical diagnoses of heart diseases. However, the use of conventional ECG system is restricted by the physical size of the unit and the system's limited transmission capacity. A patient's mobility is severely limited in this system [101]. Advanced wireless ECG systems based on our approaches would be able to deliver healthcare not only to patients in the hospital and medical centers but also in their homes and workplaces thus offering cost saving and improving the quality of life. Long-term records of ECG signals in WBANs are being kept concerning the heart for diagnostic and therapeutic purposes. That is why the quantity of data grows significantly, and compression is required for reducing the storage, transmission times, and power consumption [102]. The ECG signals generally illustrate the redundancy between adjacent heartbeats due to their semi-periodic structure. It is evident that this redundancy provides a high degree of common support between consecutive heartbeats making them a good candidate for compression. The wireless ECG systems based on CS theory provide new wireless healthcare systems with low data rate, very small transmitting power requirement, and longer battery life for diagnostic and therapeutic purposes. The proposed algorithms present our contribution of CS approach with BSBL framework, SMS procedure, DTA approach, and LCDP algorithm to establish a robust sampling procedure for wireless ECG systems. The wireless ECG systems based on our algorithms can offer two major advantages compared to current health monitoring systems. The first advantage is the mobility of patients due to the use of ambulatory health monitoring systems. Secondly, one can control and investigate ECG signals from outside of hospital and medical centers in order to increase the ability of early diagnosis and prevention. By this convenient means, elderly people can keep track of their health conditions on their Smart phones or any portable device without frequent visits to the doctor's office [103]. The wireless ECG systems based on our new sampling procedure also provide good background to serve the goal of reducing healthcare costs by monitoring several patients simultaneously. Wireless ECG systems play an important role in remote cardiac patient monitoring, intelligent emergency care management systems, and ubiquitous wireless healthcare applications. The wireless ECG systems provide vital information concerning the heart to physicians and doctors at anytime and anywhere by removing the constraints of time and location of patients while increasing both the mobility and the quality of healthcare systems. Generally, the ECG signal includes P-wave, QRS complex, T and U-wave [104]. Figure 4.5 illustrates the regular ECG signal. The irregular ECG signal has narrow and wide-QRS complexes.

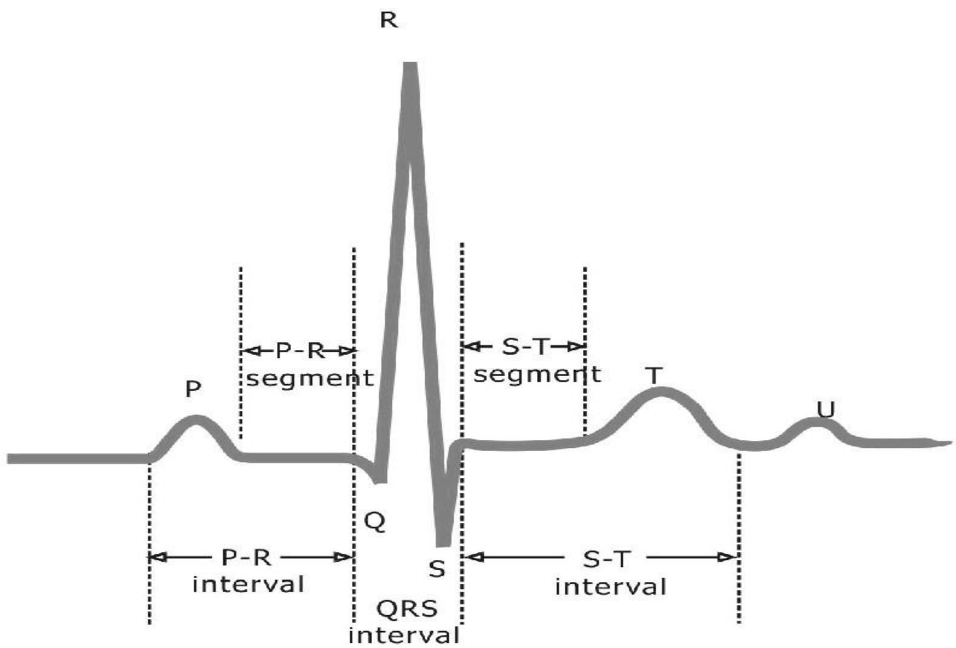


Fig.4.5: Regular ECG signal [105]

The R-wave of the QRS complex has the most important heart information of each cardiac cycle of the ECG signal. In the wireless ECG systems the BWSs collect and transmit the vital signals of cardiac patients wirelessly. The current ECG systems not only restrict a patient's mobility but are limited because of their size, power and transmission capacity [106]. Therefore, the current ECG systems need to be further developed in order to achieve extended mobility and wireless monitoring of several patients at the same time. The BWSs collect cardiac signals from patients and transmit them to gateways and access points for long-term records. Since monitoring usually continues for a rather long period of time, the quantity of data grows quickly. Therefore, it is important to compress the data to reduce the storage usage, transmission times, and power consumption. In addition, the recovery of sparse signals allows for a sampling-rate significantly below the classical Nyquist-rate [107]. The ECG signal generally detects the redundancy between adjacent heartbeats due to the semi-periodic structure [107]. Furthermore, by allowing several patients to be monitored simultaneously, the new system reduces the related healthcare costs [108]. According to the CS theory a small number of random linear measurements of bio-sparse signals contain enough information to collect, process, transmit, and recover the original signal. Figure 4.6 shows wireless ECG systems based on CS theory that show that ECG signals are compressed by biomedical wireless sensors. The collected and compressed ECG biomedical data are then transmitted wirelessly to APs at the hospital, ambulance, and helicopter [109, 110] via GW. The APs recover compressed biomedical data for diagnostic and therapeutic purposes.

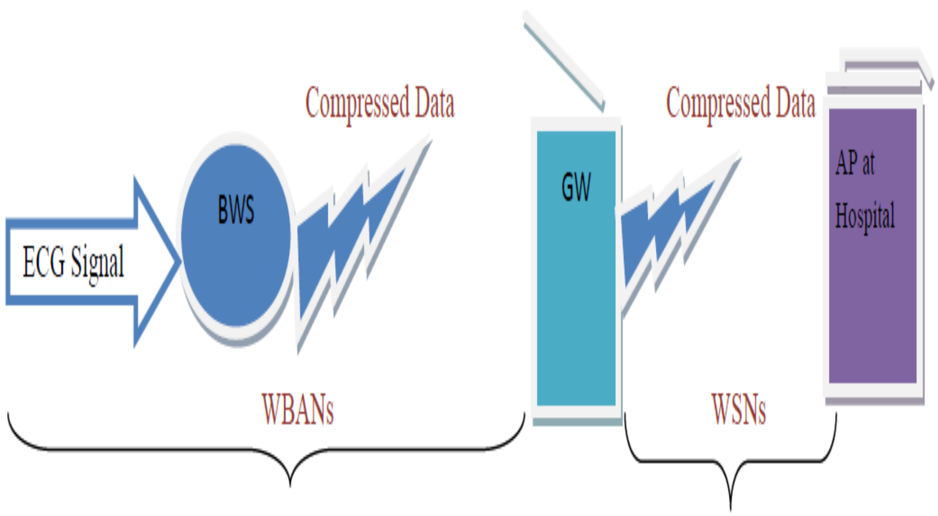


Fig.4.6: Wireless ECG systems based on CS theory

The wireless ECG systems employing the proposed algorithms offer two major advantages over the current health monitoring systems: 1) it does not restrict user's mobility; 2) it allows monitoring of ECG signals outside hospitals and medical centers which, in turn, contribute to early diagnosis. Using such a convenient tool, individuals with heart conditions and elderly people can keep track their health conditions on a portable device such as Smart phone without the need for frequent visits to their doctor's office.

4.5.1.1. Reconstruction Algorithm

We suggest integration of a BSBL framework and CS approach to compress any normal or abnormal ECG signal, including sparse and non-sparse signals, to achieve better performance [111]. The BSBL framework explores the intra-block correlation (correlation of entry values within each block). This framework is able to recover non-sparse signal with or without block partition. The BSBL framework partitions the ECG signal into a concatenation of non-overlapping blocks, and a few non-zero blocks. More specifically, the number of non-zero blocks is the same as the number of random linear measurements in the CS approach. This approach can trim blocks in abnormal ECG signals. Therefore, if abnormal ECG signals have no clear block structure, the BSBL framework and the CS theory are still effective for compressing and recovering the signals. The CS based on BSBL framework can compress normal and abnormal ECG signals at the transmitter side. To generate an approximate real-time transmission for collected ECG signals, each block should be short. At the same time, we want to incorporate as many heartbeats into one block to recover the ECG signal with fewer samples. Table 4.3 illustrates the entire Algorithm I based on CS theory and BSBL framework.

Table 4.3: Proposed Reconstruction Approach

Algorithm I : Reconstruction Approach for normal and abnormal ECG signals based on CS theory and advanced BSBL framework
Require: Matrix $[\Theta]=[\Phi][\Psi]$, Number of random measurements (M), block distance d_0, and number of non-zero blocks $\{i\}_{0\prec i\prec M}$.
1: Initialize $i=0$.
2: $[\Theta]_0$ is constructed by selecting the columns of Θ in d_0.
3: Find C_0 by solving $C_0=\arg\min_C \|\mathbb{C}-\Theta_0 C\|_1^2$
4: Calculate the following features: $R_0=\mathbb{C}-\Theta_0 C_0, CR_0=R_0/\mathbb{C},$ $PRD_0=\|R_0\|_2/\|\mathbb{C}\|_2$
6: $i=i+1$
7: Solve $C_i=\arg\min_C \|\mathbb{C}-\Theta_i C\|_1^2$

8: Calculate the following features: $R_i = \mathbb{C} - \Theta_i C_i, CR_i = R_i / \mathbb{C}, PRD_i = \| R_i \|_2 / \| \mathbb{C} \|_2$
9: Apply learning rules for Υ_i, β_i to estimate C
12: Reconstruct $[D] = [C][\Psi]$

4.5.1.2. SMS Algorithm

In CS, the random measurement matrix $[\Phi]$ is a key component for compressing the input signals [112]. Two key features are needed for the successful implementation of CS approach: sparsity of the biomedical signal should have a high degree of incoherence between the sparsity basis $[\Psi]$ and random measurement matrix $[\Phi]$. In this part we explain the new SMS procedure for selecting the best fit for the random sensing matrix $[\Phi]$. Bernoulli Toeplitz, Gaussian Circulant, and Binary Toeplitz matrices are examined to find out the best fit for random sensing matrix [113]. In the current simulation, CS approach is applied to the ECG data obtained from Massachusetts Institute of Technology- Beth Israel Hospital (MIT-BIH) database for three sensing matrix possibilities: 1) Bernoulli Toeplitz matrix, 2) Gaussian Circulant matrix, and 3) Binary Toeplitz matrix. Our simulation results confirm that the Binary Toeplitz matrix shows superior performance for the random sensing matrix Φ. Table 4.4 illustrates the novel algorithm II for selecting the best fit for Φ:

Table 4.4: SMS algorithm

Algorithm II: The Best Fit for Random Sensing Matrix Φ
Enter: Raw ECG data
1: Apply Dynamic Thresholding Approach to Raw ECG data
2: Select Initial Square Matrix
3: Apply Row Selection Scheme (select the first *M* rows as the initial sensing matrix Φ)
4: Compare with Binary Toeplitz Matrix
5: If Φ is Binary Toeplitz Matrix Stop, the Algorithm is completed
6: *M*=*M*+1
7: Go to Step 4

In Step 1 of the proposed algorithm, the DTA procedure is applied to the raw ECG data. The principal objective of the DTA is to vary the sparsity level of a raw ECG signal to a convenient level [114]. In Step 2, the initial square matrix is used for each of the sensing matrices in the experiment. In Step 3, a Row Selection Scheme (RSS) is applied to reduce the number of rows from *N* to *M*. Two RSSs approaches are compared: 1) select first M rows from the initial $N \times N$ matrix, and 2) randomly select M rows from the initial $N \times N$ matrix. Since the first RSS approach demonstrated better performance than the second RSS approach, only the first RSS approach is utilized in the proposed algorithm [115].

4.5.1.3. Detection Algorithm

The reliability of the wireless ECG systems is particularly important to ensure that gateways and APs receive ECG signal with high accuracy. In this section, we present a simple but highly reliable detection algorithm for the wireless ECG system. Generally, the ECG signal consists of P-wave, QRS complex, T-wave and U-wave. The abnormal ECG signal has either narrower or wider QRS complexes [116, 117]. Within each cycle of ECG signals the R-wave of the QRS complex contains the most important information. The proposed algorithm consists of two Stages: 1. feature extraction, which includes digital filtering and linear transformation, and 2. Decision-making stage to locate R-peak [118]. The digital filtering limits the filtering operation to just once. The decision-making stage uses ATM. The threshold value depends on RP-intervals and R-peaks and is updated periodically based on ECG features [119]. The HM for the feature extraction stage and the PFS for the decision-making stage are applied to simulate the highly reliable detection algorithm. The output signal of the filtering process with HM is bipolar. Therefore, the signal is rectified to prevent detection errors where signals change polarity. By employing the SET in the feature extraction stage, the energy values E_s smaller than the threshold is set to zero and other energy values are retained [120, 121]. Table 4.5 illustrates the proposed Algorithm.

The adaptive-threshold is defined as:

$$A_T = 0.25(1/M\sum_{n=1}^{M}(E_s[n]-E)^2)^{1/2}, \tag{4.43}$$

where M is the number of random measurements in CS, and E is commuted as:

$$E = 1/M\sum_{n=1}^{M} E_s[n]. \tag{4.44}$$

The energy threshold is proposed as:

$$E_{th} = \begin{cases} E_s \text{ if } E_s \le A_T \\ 0 \text{ otherwise} \end{cases}. \tag{4.45}$$

Table 4.5: Detection algorithm for wireless ECG systems

<table>
<tr><th colspan="3">Algorithm III: Detection Algorithm</th></tr>
<tr><td colspan="3">1) Received ECG signal at GW</td></tr>
<tr><td rowspan="2">2) Feature Extraction Stage

Target: Determine the approximate location of ECG segments</td><td colspan="2">- Digital Filtering
- Energy Transformation</td></tr>
<tr><td>Tools</td><td>1) Hamming tool
2) Shannon Energy transformation code in C++ to accentuate the ECG parts</td></tr>
<tr><td rowspan="2">3) Decision Stage

Target: Recognize the accurate location of the ECG parts, including QRS complex part</td><td colspan="2">- Peak Finding Schemes
- Peak Clipping</td></tr>
<tr><td>Tools</td><td>1)Peak finding code in C++
2)Peak clipping code in C++</td></tr>
<tr><td colspan="3">3) Detect ECG features for medical purposes</td></tr>
</table>

In the PFS step, peak clipping is employed to minimize deviation between the detected peaks of the ECG signal. The peak clipping adaptive threshold is illustrated as:

$$P_T = 0.1 \times \max(E_{TH}). \tag{4.46}$$

Then, the peak clipping is performed with the following equation:

$$P_C = \begin{cases} E_{TH} \text{ if } E_{TH} \le P_T \\ P_T \text{ otherwise} \end{cases}. \tag{4.47}$$

In the SET step, the Shannon Energy (SE) of the normalized ECG is determined as [122]:

$$SE = -ecg[n] \ \log (ecg[n])^2 . \tag{4.48}$$

The average value of the filtering is adjusted based on the SE values to determine the approximate location of the segments in the ECG signal. Finally, a True Peak Locator (TPL) of PSC approach is employed to accurately extract the main features of the ECG signal.

4.5.2. Performance Measure

The MIT-BIH database is used to evaluate the performance of the compression procedure [123]. This database is the most commonly referred to for the comparative research of ECG compression approaches. This database has the following features:

► 48 half excerpts of two-channel ambulatory ECG recording;

► 360 samples per second channel with 11-bits resolution over a 10-mv range;

► Tested on 47 subjects

► Defined by the BIH arrhythmia laboratory

The Compression Ratio (CR), the Structural Similarity Index (SSI), and PRD are employed as performance measures in our approach. The CR is found as follows:

$$CR = N / M \times 100 , \tag{4.49}$$

where M and N are the number of random linear measurements and the number of samples in ECG signals, respectively. Further, our simulation results indicate that satisfying the quality of *SR* can be achieved when *CR* does not exceed of 35%. The SSI metric is defined as:

$$SSI = (\mathbb{C} / D) \times 100 , \tag{4.50}$$

where D and $\mathbb{C}$ are the original and recovered ECG signals, respectively. This metric measures the similarity between the recovered and original ECG signals. Higher *SSI* means better recovery quality. Our simulation results will show the proposed approach has this ability to achieve *SSI* with a value close to 100%. The PRD is computed as [124]:

$$PRD = (\| D - \mathbb{C} \|_2 / \| D \|_2) \times 100 , \tag{4.51}$$

The value of PRD shows the quality of reconstruction approaches. The relationship between the measured PRD and diagnostic distortion is recognized according to the weighted diagnostic data for ECG signals which classifies the different values of PRD based on the signal quality obtained by a specialist.

4.6. Simulation Results

In this section, the simulation results for three algorithms are investigated. For algorithm I, the features of ECG signals such as *CR*, *SNR*, and *PRD* are simulated. For algorithm II, features of random sensing matrix are illustrated. For algorithm III, the sensitivity percentages and detection accuracy percentages for the received compressed ECG signals are presented. Our simulation results illustrate a 25% reduction of PRD and a good level of quality for Signal to Noise Ratio (SNR). The simulation results also confirm that the Binary Toeplitz matrix provides the best SNR and compression performance with the highest energy efficiency for random sensing matrix in the CS scenario. Our simulation results also show an increment of 10% for sensitivity, 15% for the prediction level, and good detection accuracy in gateways and access points in hospitals and medical centers. The simulation results validate the suitability of the new algorithm for a real-time energy-efficient ECG compression using resource-constrained WBANs. The proposed algorithm also achieves a significantly better detection rate when compared to the Empirical Mode Decomposition (EMD) method. The following assumptions were made for the simulation:

► Experiments are carried out from a 10-minutes ECG signal from MIT-BIH database.

► One hundred repletion's are averaged for our simulation results. To validate the simulation results, ECG signals from records 100,107,115 and 117 of MIT-BIH are investigated.

►The mean of ECG blocks is rounded in the sliding window to the nearest multiple of 2^L, where L is the BSBL level.

►To simulate *SNR* for ECG signals the following equation is used:

$$SNR = -20\log_{10}(0.01PRD)\,. \tag{4.52}$$

►The implementation of sensing matrix $\Phi^{M\times N}$ is simulated for Gaussian distribution, sparse binary sensing, and uniform distribution.

►The sparse sensing matrix with non-zero entries equal to $\pm 1/\sqrt{2}$ is used for the sparse binary matrix.

►The permissible parameters were adopted from IEEE802.15.3, IEEE802.15.5, and IEEE802.16e protocols, which support low power communication in WBANs.

►The random sensing matrix $\Phi^{M\times N}$ is applied to all the records of the MIT-BIH ECG database.

►The SPGL1 (Spectral Projected Gradient for L1 minimization) toolbox is used to determine Large-scale one-norm regularized least squares in the following equation:

$$\min_{c \in \mathbb{R}^N} \| c \|_1 \text{ subject to } \mathbb{C} = \Phi D \quad . \tag{4.53}$$

►To validate the simulation results, the BPBQ (Basis Pursuit DeQuantizer) toolbox is used for recovery of sparse signals from quantized random measurements to solve:

$$\arg\min_{c \in \mathbb{R}^N} \| c \|_1 \text{ subject to } \| \mathbb{C} - \Phi D \|_p \text{ for } p \geq 2 . \tag{4.54}$$

►The simulation results were obtained for an input signal of *N=512* samples and a 12-bits resolution for the input signal and the measurement signal $\mathbb{C}$. The random binary matrix is applied to all the records of the MIT-BIH ECG database to optimize the number of non-zero entries to simulate SNR.

►To simulate the SMS approach, the DTA framework is used to vary the sparsity level.

4.6.1. Simulation Results on reconstruction algorithm

In this section, the proposed reconstruction algorithm based on BSBL framework is applied to improve SNR, CR, SR, PC, and quality of the recovered ECG signals. Fig. 4.7 shows that a satisfying quality for SNR can be achieved by minimizing CR that would, in turn, result in an increase in the number of non-zero elements. The output SNR becomes saturated after the number of non-zero entries *M=15*, which is the reference value for the rest of simulation results. To compare the performance quality for the recovered ECG signal, the random Gaussian and random binary matrices are employed as a sensing matrix Φ. Our simulation results show the shortest execution time for a random binary matrix. The execution time for random Gaussian matrix is 2s, while for random binary matrix it is 8 ms. The simulation results on SR and PC, based on the MIT-BIH ECG databases in non-CS and CS scenarios are presented here. For this simulation, the following assumptions are made:

► Total number of coefficients N =1024, 2048, 3072.

► K : number of non-zero coefficients.

► M : number of random linear measurements.

► c: constant =1.5 in the $M \geq cK \log(N / K)$ in order to calculate M .

► Nyquist Rate (NR) =2* N =2048, 4096, 6144.

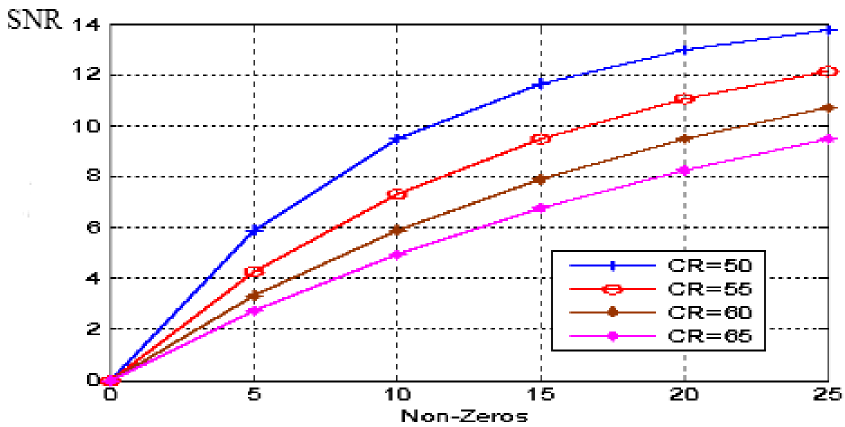


Fig.4.7: SNR in terms of non-zero entries

Figure 4.8 shows the results on reduction of SR for N =1024, N=2048, N =3072.

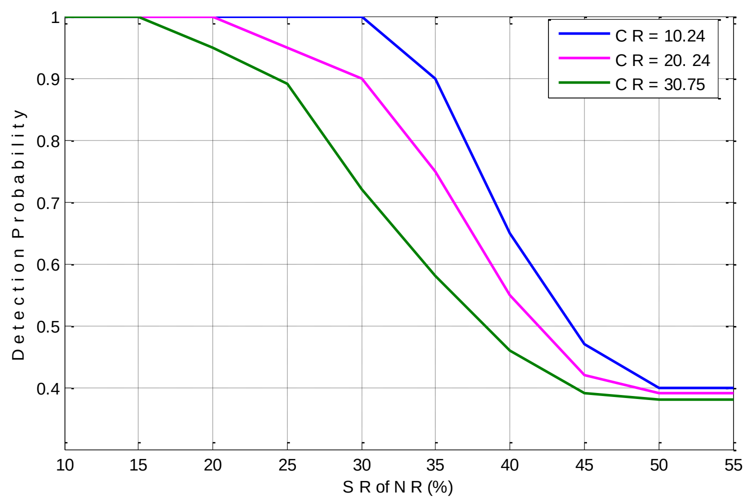


Fig.4.8: Detection Probability for ECG signals versus SR

As depicted in Fig. 4.8, the sampling rate can be reduced by 75% of NR without sacrificing the performance. Power management in a WBAN is a very important operational issue. The power consumption can be divided into the three domains of sensing, communication, and data processing. The power available in wireless nodes is often restricted. The power consumption of a WN could be minimized by increasing the probability of successful packet transmission. The power consumption by the wireless nodes can also be reduced by applying CS to WBANs. The CS theory will thus be used to extend the life of each wireless node. The ideal WBANs are networked and scalable nodes that consume very limited power. The CS theory can increase the sleep time of processing and communication units by decreasing the sampling-rate. Therefore, it is possible to communicate data only when required. Figure 4.9 shows simulation results regarding power consumption in terms of CR for three ECG signals.

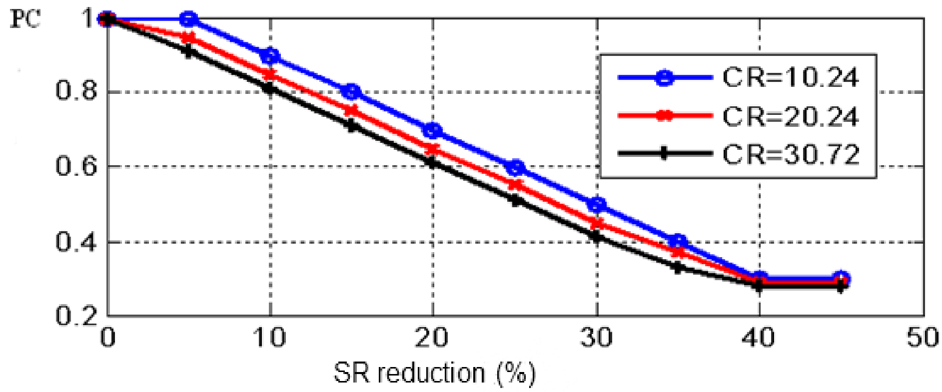


Fig.4.9: Power consumption versus SR

It can be seen, the power consumption can be reduced by employing CS theory. Table 4.6 compares the simulation results concerning sampling rate and power consumption for three different ECG signals. Satisfying sampling rate and power consumption can be achieved when CR is less than 30.

Table 4.6: Comparing SR and PC

***N* in ECG**	**CR**	**SR**	**PC**
1024	10.24	25%*(NR)	30%*(PC in non-CS)
2048	20.48	28%*(NR)	35%*(PC in non-CS)
3074	30.74	32%*(NR)	40%*(PC in non-CS)

Table 4.7 compares *CR*, *SNR*, and number of non-zero entries in order to illustrate *M* saturated value.

Table 4.7: *M* saturated value

CR (%)	**Number of non-zero elements(M)**	**SNR**
45	≥ 15	22
50	≥ 15	19
55	≥ 15	16
60	≥ 15	14
65	≥ 15	12
70	≥ 15	10
75	≥ 15	6
80	≥ 15	3

Figure 4.10 shows the simulation result only for record of 117 ECG from the ECG database in terms of PRD in non-CS and CS theory scenarios.

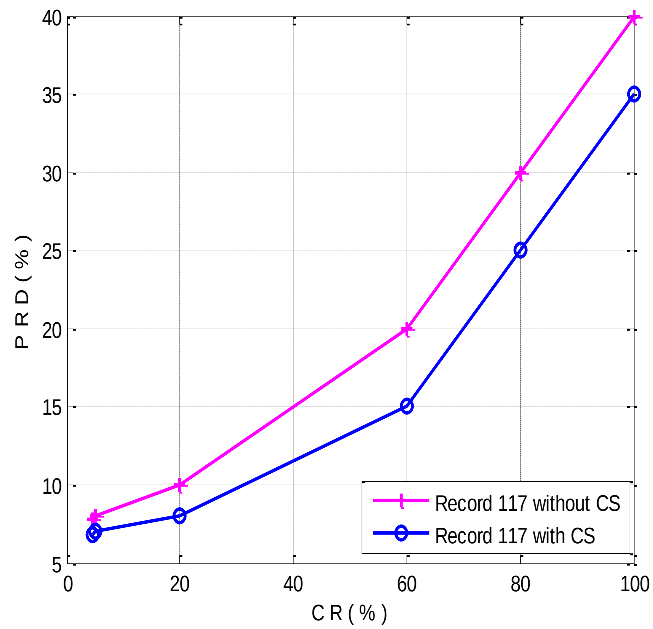


Fig.4.10: ECG record 117 with CS and non-CS scenarios

As shown in Fig.2.10, by applying CS theory percentage, the root-mean square difference is decreased. This ability allows improving quality of reconstruction algorithm.

Reliability of a WBAN is directly related to the packet loss probability and packet transmission delay. The packet loss probability is influenced by the BER of a recovered ECG signal for diagnostic and therapeutic purposes. The simulation results show that CS can reduce the effective BER by using an adaptive sampling procedure to suit the transmission channel conditions. This process will result in an increase in the higher packet transmission. Higher packet transmission success probability reduces the packet delay as well as the power budget of an ECG signal. The power budget could be optimized by increasing the probability of successful packet transmission. The CS theory decreases BER for a recovered ECG signal. Our simulation results show this ability can minimize BER by 10%. Figure 4.11 compares BER of recovered ECG signal in non-CS and CS scenarios for a random sensing matrix. The simulation results indicate that an acceptable level for BER can be achieved when CS is employed in ECG signals.

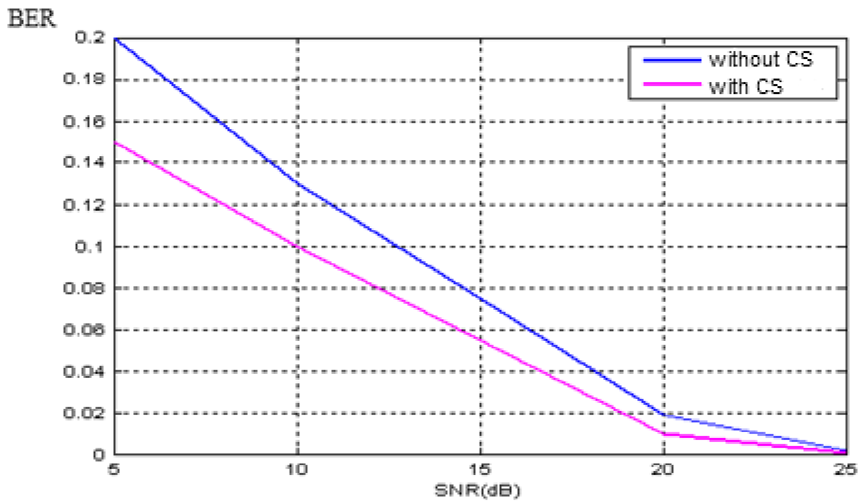


Fig.4.11: BER with CS and non-CS

4.6.1.1. Simulation Results on Sampling Rate in ECG Signals in terms of *M*

Our simulation results in this section show that the sampling-rate in ECG signals can be reduced to 25% of the Nyquist-rate without sacrificing performance of the ECG signals. However, when further decreasing the sampling-rate, the performance is gradually reduced. In this simulation, we used 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 equation:

$$\begin{cases} M \geq cK \log N / K \\ K \leq M \ll N \end{cases} . \tag{4.55}$$

►c as a constant =1.5.

►Nyquist-rate=2048.

►Random linear measurements have Gaussian distribution.

►Compressed Ratio is defined as $CR = N / M$.

Figure 4.12 shows simulation results, and Table 4.8 shows the results for *K=100*, *K=200*, *K=300*. Consequently, the sampling-rates are reduced by applying the CS theory to some signals in WBANs.

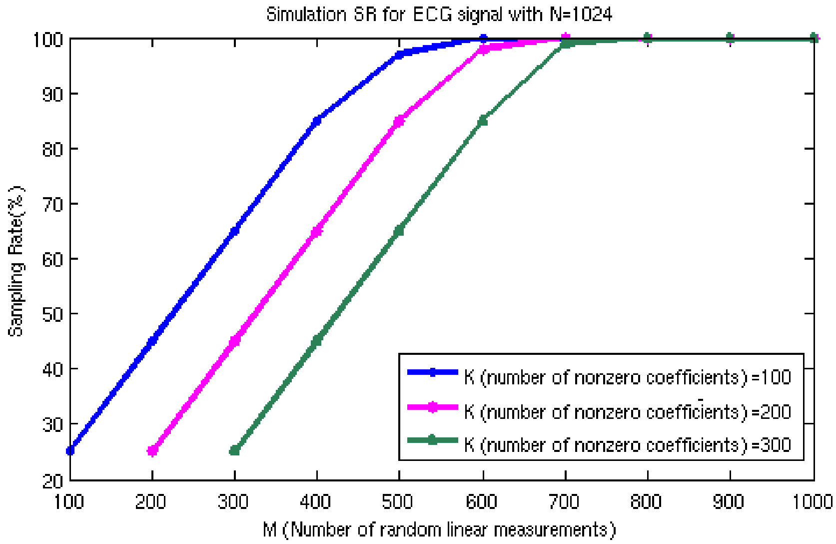


Fig.4.12: The simulation of SR for K=100, K=200, K=300

Table 4.8: Simulation results

Number of non-zero coefficients (K)	Number of random measurements	SR in ECG signal compared with N.R
100	100-500	25-100%
200	200-580	25-100%
300	300-700	25-100%

4.6.1.2. **Simulation Results on Power Consumption in ECG Signals in terms of CR**

The power consumption is the most important factor in determining the lifetime of a wireless node, because the power supply of wireless nodes has very low energy. This makes power optimization more complicated in WSNs because it involves not only reducing power consumption but also prolonging the life of the network as much as possible. Regarding the application of WBANs, it is impossible to gain physical access in order to change or recharge the power supply. Therefore, each wireless node must be designed to manage its power supply. The CS theory is capable of minimizing power consumption. The simulation results are produced using the simulator developed in C^{++}.

The simulation results are shown in Table 4.9 and compared with a non-CS network. Figure 4.13 shows simulation results concerning power consumption in terms of Compressed Ratio (*CR=N/M*) for ECG signals in WBANs with the CS theory.

Table 4.9: Simulation Results on Power consumption

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

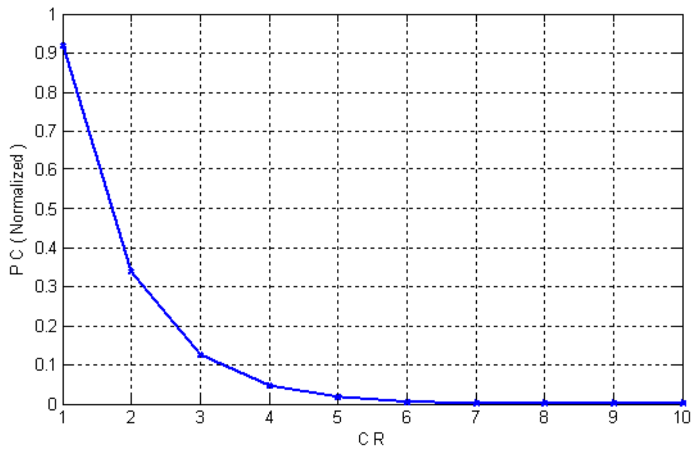


Fig.4.13: Simultion results on power consumption in ECG

Power consumption is the most important factor to determine the life of a biomedical sensor because such sensors are usually driven by a battery that has very low power resources. To expand the applications of WBANs to EH, MH, and AHMS, power consumption and (D) should be kept at a minimum value. Our results show that by employing the CS, WBANs can achieve a higher transmission, a low time delay, and a high probability of success in data transmission. It is clear that a combination of CS theory applied to WBANs is the optimal solution for achieving robust low-power WBANs.

From the simulation results, we investigated that the sampling-rate in ECG signals can be reduced to 25% without sacrificing performance. Table 4.10 summarizes the results for SR and PC.

Table 4.10: Results for SR and PC

Number of measurements (M)	Number of samples N=1024	Number of samples N=2048	Number of samples N=3072
100	CR=10.24 SR $\rightarrow$ 25% PC $\rightarrow$ 30%	CR=20.24 SR $\rightarrow$ 25% PC $\rightarrow$ 30%	CR=30.72 SR $\rightarrow$ 25% PC $\rightarrow$ 30%
200	CR=5.12 SR $\rightarrow$ 27% PC $\rightarrow$ 33%	CR=10.24 SR $\rightarrow$ 27% PC $\rightarrow$ 33%	CR=15.36 SR $\rightarrow$ 27% PC $\rightarrow$ 33%
300	CR=3.41 SR $\rightarrow$ 30% PC $\rightarrow$ 35%	CR= SR $\rightarrow$ 30% PC $\rightarrow$ 35%	CR= SR $\rightarrow$ 30% PC $\rightarrow$ 35%
400	CR=2.04 SR $\rightarrow$ 33% PC $\rightarrow$ 37%	CR= SR $\rightarrow$ 33% PC $\rightarrow$ 37%	CR= SR $\rightarrow$ 33% PC $\rightarrow$ 37%

Finally, the proposed algorithm is applied to the reconstruction of ECG signals at the receiver side. As we proposed, the reconstruction algorithm relies on a combination of CS theory and an advanced BSBL framework for recovering the biomedical signals that are sparse in terms of either the number of non-zero samples or non-zero blocks. In the advanced BSBL framework, i is defined as the number of non-zero blocks; and in CS theory, M is the number of random measurements. Figure 4.14 demonstrates the recovered signal when the number of nonzero blocks i is less than the number of random linear measurements M . Figure 4.15 illustrates the recovered signal when $i = M$ and Figure 4.16 shows the recovered signal for $i \succ M$. Therefore, the best quality of the reconstruction signal is achieved when the number of non-zero blocks is the same as the number of random linear measurements.

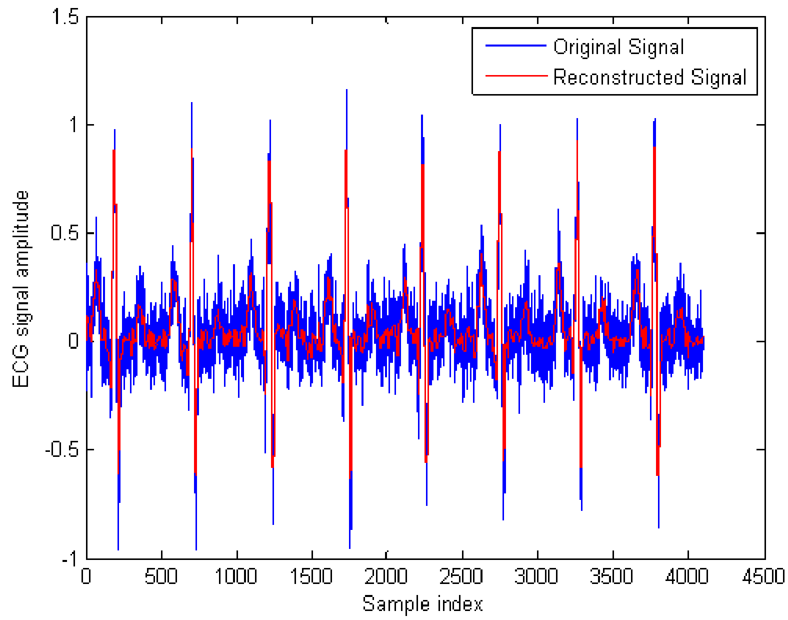


Fig.4.14: Recovered signal for $i \prec M$

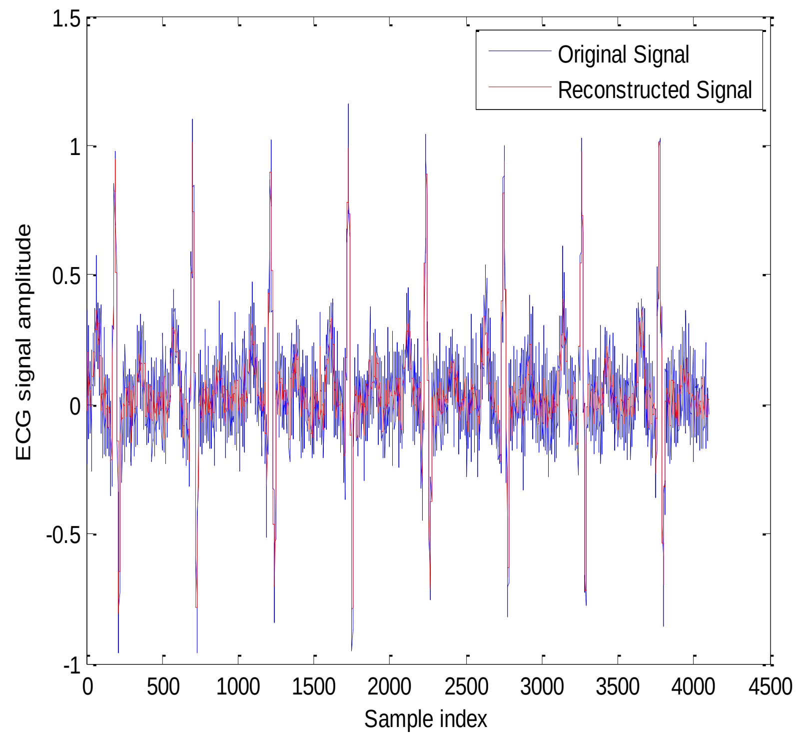


Fig.4.15: Recovered signal for $i = M$

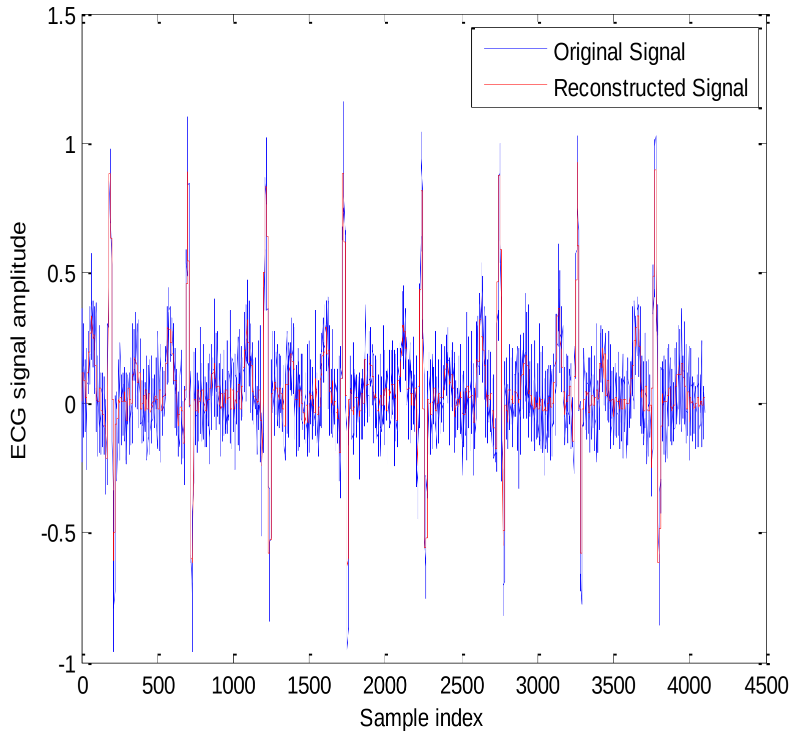


Fig.4.16: Recovered signal for $i \succ M$

As expected, the best quality of reconstruction is achieved when the number of non-zero blocks is the same as the number of random measurements.

4.6.2. Simulation Results on SMS Algorithm

In the current simulation, CS approach is applied to the biomedical data obtained from MIT-BIH database for three sensing matrix possibilities: 1) Bernoulli Toeplitz matrix, 2) Gaussian Circulant matrix, and 3) Binary Toeplitz matrix. Our simulation results will confirm that the Binary Toeplitz matrix shows the best performance for the random sensing matrix Φ. Our simulation results indicate that satisfying the quality of *SNR* and *CR* can be achieved when the Binary Toeplitz matrices are selected for the random sensing matrix Φ. The Binary Toeplitz sensing matrix with non-zero entries is considered for Φ in order to decrease execution time during the simulation process. The random binary matrix Φ has M non-zero entries equal to 1, with $M \ll N$. The mutual coherence $\mu(\Phi, \Psi)$ as an important parameter between random matrixes Φ and the sparsity basis Ψ is decreased by increasing the number of non-zero entries in matrix Φ. Figure 4.17 illustrates the mutual coherence versus the number of non-zero entries for three matrices of Φ.

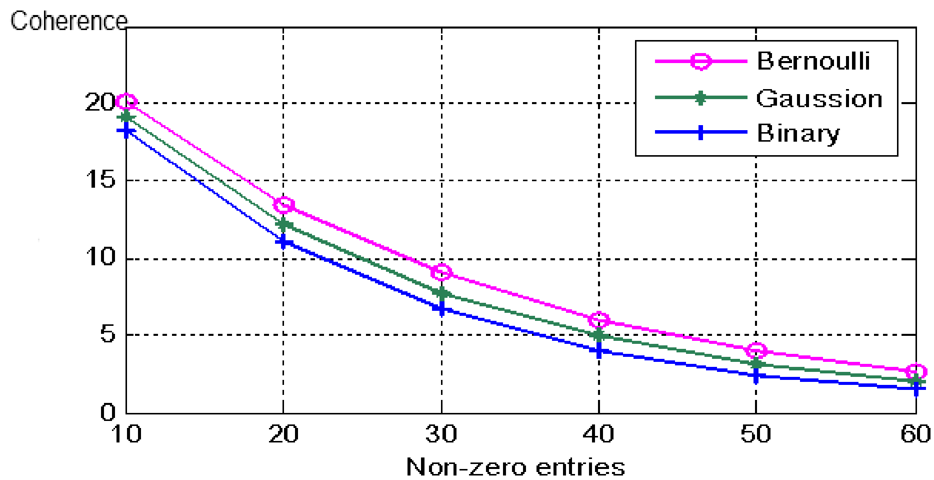


Fig.4.17: Mutual coherence $\mu(\Phi,\Psi)$

Based on the results of Fig. 4.17 and the suitability of the random binary matrix, this matrix is applied to all the records from the MIT-BIH ECG database to optimize the number of non-zero entries in the SNR simulation. Figure 4.17 reports the resulting average output SNR in terms of the number of non-zero elements in the random binary matrix Φ. This allows the random binary matrix to achieve a better performance in recovering the original ECG signal. Figure 4.18 illustrates *CR* versus *SNR* for random Gaussian and binary matrices.

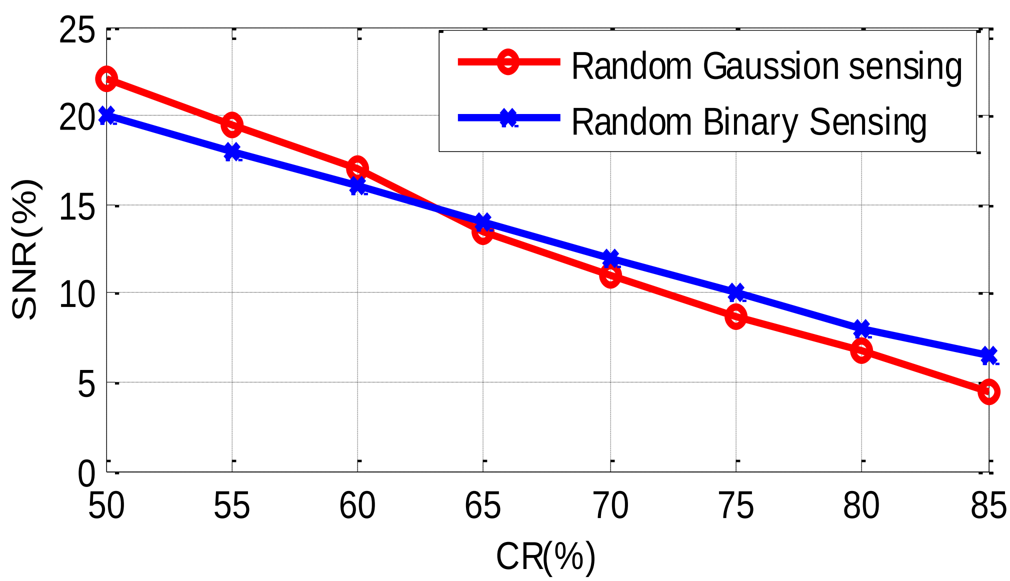


Fig.4.18: The comparison for random and Gaussian matrix

As depicted in Fig. 4.18, the random binary matrix exhibits excellent robustness, making it a convenient candidate for random sensing matrix Φ in the CS approach. This capability allows the simplest operation and the smallest memory footprint in hardware design. Therefore, the use of a random binary sensing matrix for Φ combined with quasi-periodic ECG signals yields excellent performance to recover the original ECG signal for diagnostic and therapeutic purposes. Figure 4.19 compares *SNR* versus *CR* for three random sensing matrices for ECG signal, which used the DTA procedure at a 98% of sparsity level. In the simulation of the algorithm proposed for the SMS approach, only ECG received signals at GW with $SNR \geq 50dB$ being categorized as successful trials.

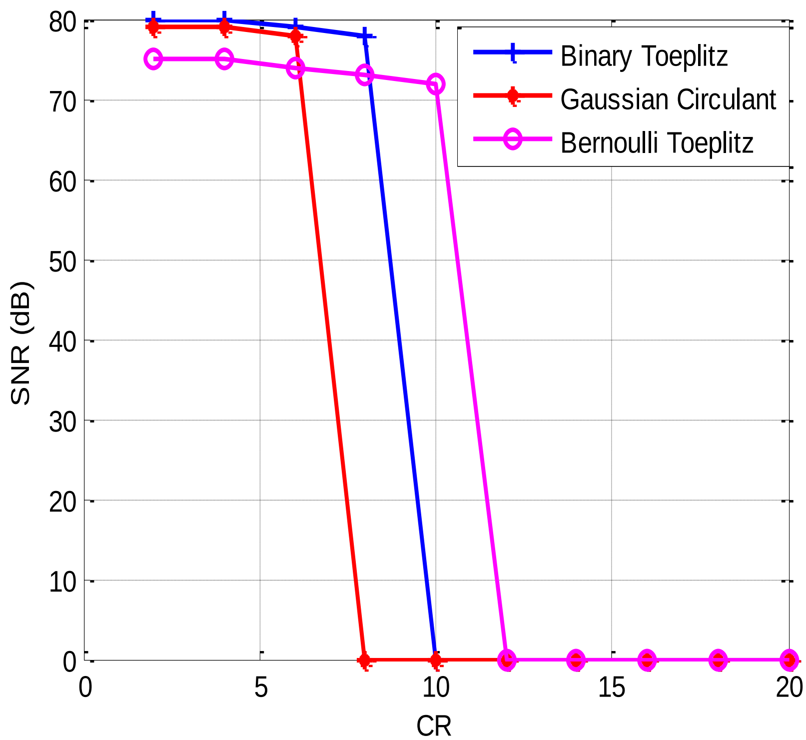


Fig.4.19: Comparison for random Gaussian, Binary, and Bernoulli matrices

As depicted in Fig. 4.19, the random binary matrix exhibits excellent robustness to be a convenient candidate for random sensing matrix Φ in CS approach. Figure 4.20 illustrates the reduction of sampling-rate for random binary matrix with CS theory in terms of detection probability.

As depicted in Fig.4.20, the sampling rate can be reduced by 75% of NR without sacrificing the performance. This capability allows the simplest operation and the smallest memory footprint in hardware design. Therefore, the use of a random binary sensing matrix for Φ combined with the quasi-periodic nature of ECG signals yields the accurate recovery of original ECG signals.

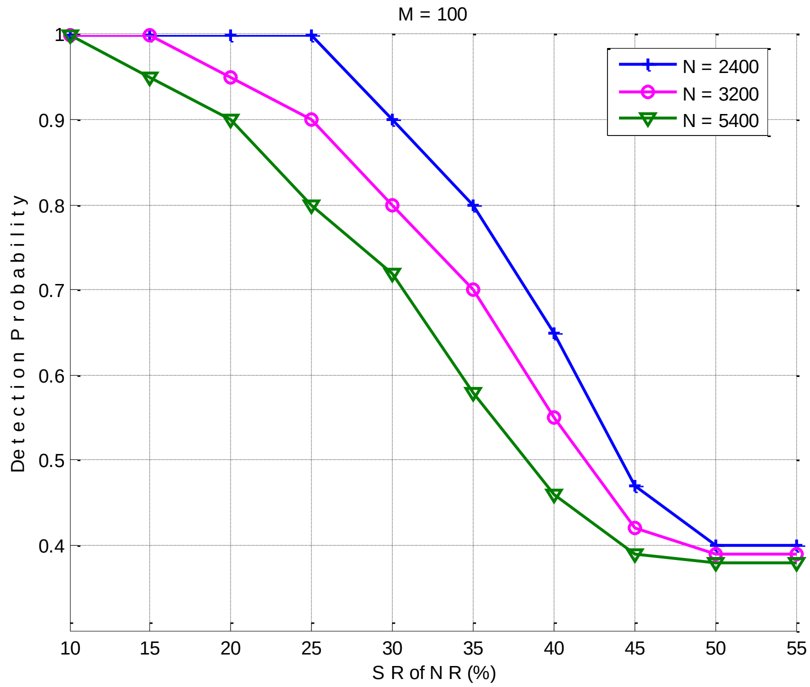


Fig.4.20: Probability of detection ECG signals versus SR

4.6.3. Simulation Results on Detection Algorithm

The proposed algorithm is applied for records 105, 108, 200, 203, and 205 of 48 half-hours 2-channel ECG recordings of MIT-BIH Arrhythmia Database, which was sampled at 360 Hz with 11-bit resolution. The Sensitivity Percentages (SP), Positive Prediction Percentages (PPP), and Detection Accuracy Percentages (DAP) are used to determine the validation of the proposed algorithm. The sensitivity can be expressed as:

$$SP\% = P_T / (P_T + N_F) \times 100, \tag{4.56}$$

where P_T and N_F are the number of positive parts and negative parts, respectively. The positive prediction is obtained by the following equation:

$$PPP\% = P_T / (P_T + P_F) \times 100, \tag{4.57}$$

where P_F denotes the number of false-positive parts. The DAP as a final measurement of the proposed algorithm is obtained from:

$$DAP\% = P_T / (P_T + P_F + N_F) \times 100. \tag{4.58}$$

The simulation results for records 105, 108, 200, 203, and 205 are given in Table 4.11.

Table 4.11: The results for selected records of ECG signal

ECG Rec.	Total Beats	P_F %	N_F %	SP %	PPP %	DAP %
105	2072	12	10	99.61	99.53	99.19
108	1763	2	0	100	99.89	99.90
200	2601	0	1	99.96	100	99.96
203	2980	3	84	97.18	99.90	97.08
205	2656	0	5	99.81	100	99.81

Table 4.12 compares the performance of the proposed algorithm with the EMD –based method. The proposed algorithm allows a better detection rate even when ECG signals contain narrow and wide QRS segments.

Table 4.12: Comparing the performance of EMD-based method and the proposed algorithm

ECG Rec.	Total Beats	N_F / EMD	N_F /Proposed Algorithm
105	2072	22	10
108	1763	22	1
200	2601	03	01
203	2980	30	04
205	2656	02	01

As depicted in Table 4.12, the proposed algorithm illustrates better detection accuracy, specifically for abnormal ECG records.

Table 4.13 compares the SP and PPP of the EMD-based method and the proposed algorithm shows significantly better SP and PPP for the proposed algorithm.

Table 4.13: Comparing the SSP and SP of EMD-based method and the proposed algorithm

ECG Rec.	SP /EMD %	PPP /EMD%	SP/P %	PPP/P %

105	99.71	99.54	99.85	99.89
108	99.89	99.91	99.94	99.93
200	99.92	99.98	99.96	99.99
203	98.10	99.90	99.11	99.96
205	99.82	99.98	99.93	99.99

Figure 4.21 illustrates the SP of the selected ECG records obtained by EMD-based method and the proposed algorithm.

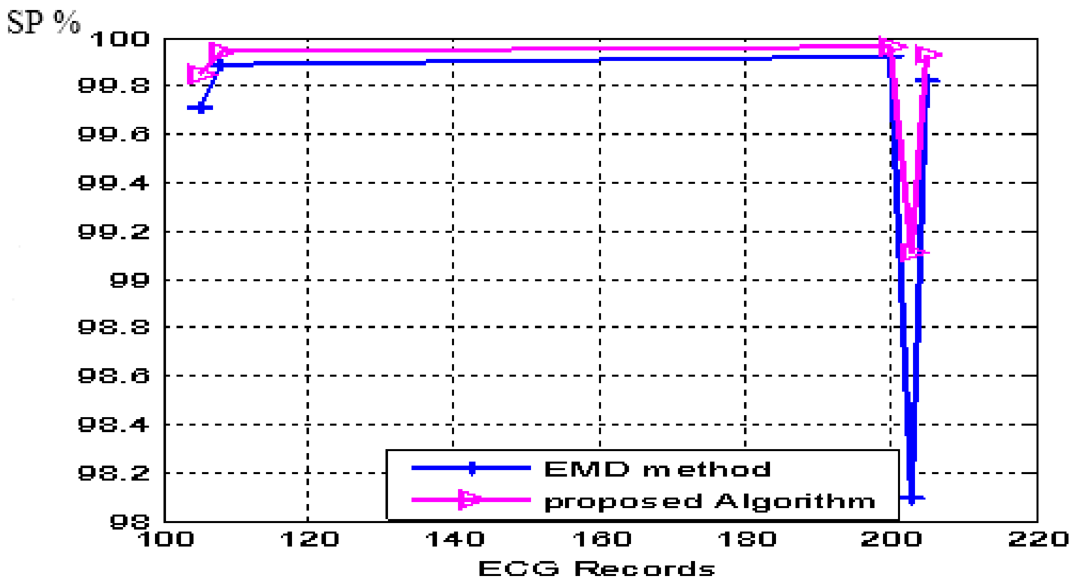


Fig.4.21: Comparing the SP of EMD-based method and the proposed algorithm

The proposed algorithm increased the sensitivity of the received ECG signal. This allows for better performance of wireless ECG systems based on CS theory. Figure 4.22 demonstrates the PPP of selected ECG records and then compares it to both EMD-based method and the proposed algorithm.

As can be seen in Fig. 4.21, the proposed algorithm shows an increase in the prediction level at gateways or access points for wireless ECG systems. The simulation result illustrates a satisfying quality of prediction level for wireless ECG systems with CS theory. Thus there is a high probability of providing the detection algorithm.

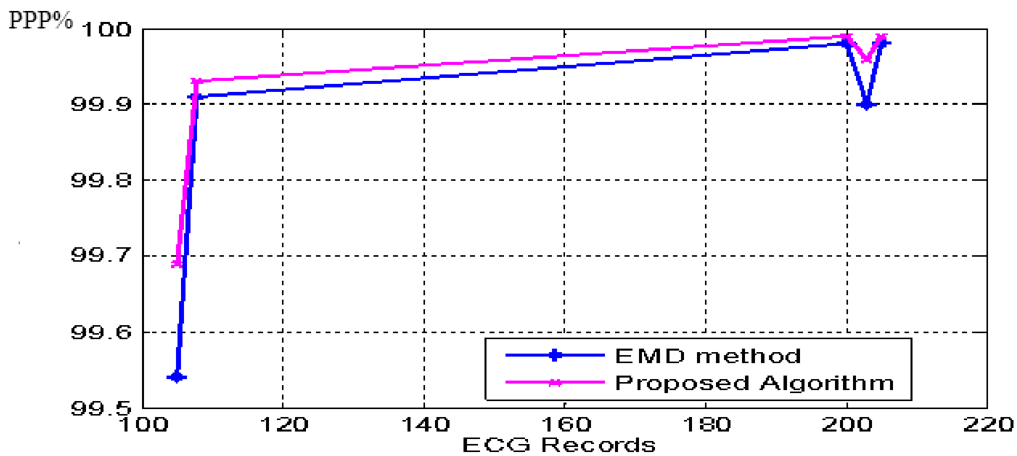


Fig.4.22: The comparative work on PPP in the EMD-based and proposed algorithm

4.7. Chapter Summary

The emerging application of CS theory in medical areas has the potential to provide low sampling-rate wireless ECG systems. However, the success of the wireless ECG system heavily relies on reducing the sampling-rate load. The ECG signal is widely used in WBANs because it is a noninvasive way to provide medical diagnosis of heart diseases. This chapter proposed a modified sampling approach based on CS theory and the integration of BSBL framework, SMS approach, and LCDP algorithm to provide a robust low sampling-rate and ultra-low-power approach for normal and abnormal ECG signals. Our simulation results illustrate a 25% reduction of PRD and a good level of quality for SNR. The simulation results also confirm that the Binary Toeplitz matrix provides the best SNR and compression performance with the highest energy efficiency for random sensing matrix within the CS scenario. Our simulation results also show an increment of 10% for sensitivity, 15% for the prediction level, and good detection accuracy in GWs and APs in the hospitals and medical centers. The simulation results also illustrate that the proposed algorithm achieves a significantly better detection rate compared with EMD-based method**.** Our simulation results validate the suitability of a new algorithm for a real-time energy-efficient ECG compression with resource-constrained in WBANs. As expected, our algorithm was found to exhibit better performance through *SNR*, *CR*, and *PRD*. We have also investigated that our new approach based on CS theory and the integration from BSBL framework exhibits the best overall energy efficiency for normal and abnormal ECG signals. This efficiency is due to its lower complexity and reduced execution time for either software or hardware.

4.8. Plan for next Chapter

In the next chapter, we apply CS theory to WBANs with more than one biomedical signal to minimize the load caused by sampling-rate and provide low-power networks. Advanced WBANs based on our algorithms will be able to deliver healthcare not only to patients in hospitals and medical centers but also in their homes and workplaces, thus offering cost saving and improving the quality of life. As an important result of these networks, patients gain more mobility and comfort in spite of medical equipment. Further applications of WBANs with CS theory introduce numerous possibilities for improving the quality of collected medical data in order to make the medical decisions for diagnostic and therapeutic purposes. The emerging application of CS theory in medical areas, including WBANs with multiple biomedical signals, has the great potential to provide low sampling-rate networks. However, the success of WBANs with multiple biomedical signals heavily relies on reducing the load of the sampling-rate. Figure 4.23 demonstrates the plan for next chapter. Based on Fig.4.20, the following contributions are applied to WBANs with N biomedical signal:

► Apply SMS algorithm at the transmitter side to find the best fit for random sensing matrix for compressing biomedical signals. The fundamental objective of this algorithm for WBANs with multiple biomedical signals is to determine whether a random sensing matrix is a good candidate matrix to ensure recovery of the original signal from the compressed signal.

►Employ a new testing algorithm at the transmitter side to increase the reliability and availability of the medical network. The benefits of applying CS theory in a new testing algorithm can be divided into three areas. The first area is to improve the quality of testing. As a result, uncovered and failed wireless nodes can be repaired or replaced before they affect network availability. The second area is to minimize the volume of data testing received by wireless nodes. Thirdly, the goal is to reduce wireless node consumption associated with the distribution of compressed test programs.

►Apply reconstruction algorithm based on a contribution of BSBL framework and CS theory to recover biomedical signals, including sparse and non-sparse cases. The main purpose of this algorithm for WBANs with multiple biomedical signals is to recover non-sparse signals with or without a block structure.

►Employ a detection algorithm to increase the detection probability for capturing the compressed signals. The reliability of the WBANs with multiple biomedical signals is particularly important to ensure that GWs and APs receive compressed biomedical signals with high accuracy. The main objective of this algorithm is to apply a simple but highly reliable detection approach at the receiver side for increasing the detection probability. This algorithm is applied at the receiver side before the reconstruction algorithm is employed.

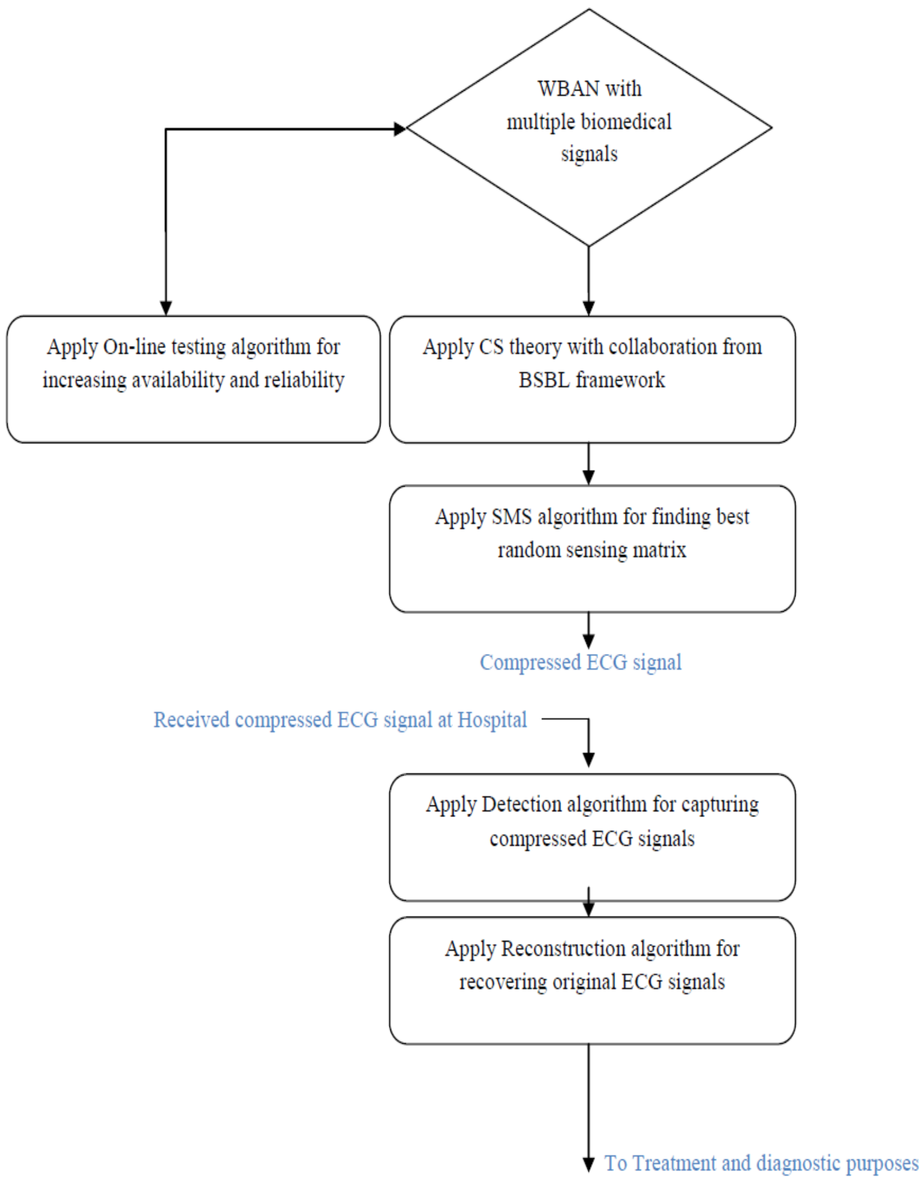


Fig.4.23: Plan for next Chapter

Chapter 5

WBANs with Multiple Biomedical Signals Based on CS Theory

5.1. Motivation

In Chapter 4, the CS theory has been applied to only ECG signals. The fundamental purpose of this chapter is to apply CS theory to WBANs with multiple biomedical signals to provide low-power and low sampling-rate wireless health monitoring systems and ubiquitous health care systems. The WBANs are expected to provide a breakthrough technology in healthcare areas such as EH, home care, telemedicine, and physical rehabilitation. To expand WBANs to these new applications, the power consumption and sampling rate should be kept to a minimum. On the other hand, WBANs are one area that has not yet explored the benefit that CS theory might provide. The benefits of using WBANs with multiple biomedical signals can be divided into two areas. One area is the use of new wireless technological solutions for individually-based, multi-parameter monitoring at home. It means patients with chronic diseases, as well as a growing number of seniors, will profit from treatment and medical monitoring at home or in the workplace. Moreover, unlimited freedom of movement assumes the use of wireless and even implanted biomedical sensors that greatly enhance home monitoring and follow-up of medical conditions. The second area of benefit is achieved by increasing the efficiency of treatments at hospital and medical centers. Advanced WBANs with multiple biomedical signals based on the algorithms in this chapter will be able to deliver healthcare not only to patients in hospital and medical centers; but also in their homes and workplaces thus offering cost saving, and improving the quality of life. As an important result of these networks, patients gain more mobility and comfort while using medical equipment. Further applications of WBANs with CS theory introduce numerous possibilities to improve the quality of collected medical data in order to make medical decisions for diagnostic and therapeutic purposes.

An application of CS theory to WBANs is the optimal solution for achieving the networks with a low-sampling rate and low-power consumption. By compressing, the data size is reduced, and fewer bandwidths are required to transmit data. The CS helps in data gathering and transferring and can change the traditional theorem and technology of wireless networks which may lead to other improvements in capacity, delay, relay nodes, routers, and loss of packets. Figure 5.1 shows our plan for this chapter.

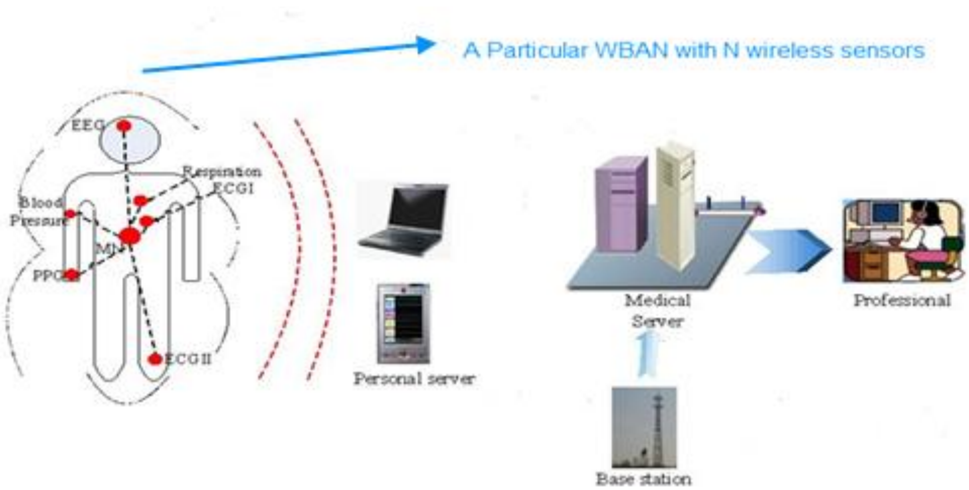


Fig.5.1: Plan for this Chapter

This chapter is organized as follows: first, the contribution for this chapter is illustrated. Second, the proposed algorithms are applied to WBANs with N biomedical signals. Finally, the simulation results are demonstrated.

5.2. Contribution

The fundamental contribution of this chapter is to apply the four algorithms to a particular WBAN. The SMS algorithm will serve as Algorithm I, new testing procedures based on CS theory as Algorithm II, the detection approach as Algorithm III, and the reconstruction Algorithm as Algorithm IV, all to be directed to a particular WBAN with N biomedical signals. The Algorithms I, III, and IV were presented in Chapter 4, while Algorithm II is presented in this chapter. Figure 5.2 shows a combination of algorithms I and II in the transmitter side. The fundamental objective of the new testing algorithm based on CS theory is to increase the reliability and availability for WBANs with *N* biomedical signals so that individual biomedical signal reliability may be measured to ensure the biomedical network is online and available.

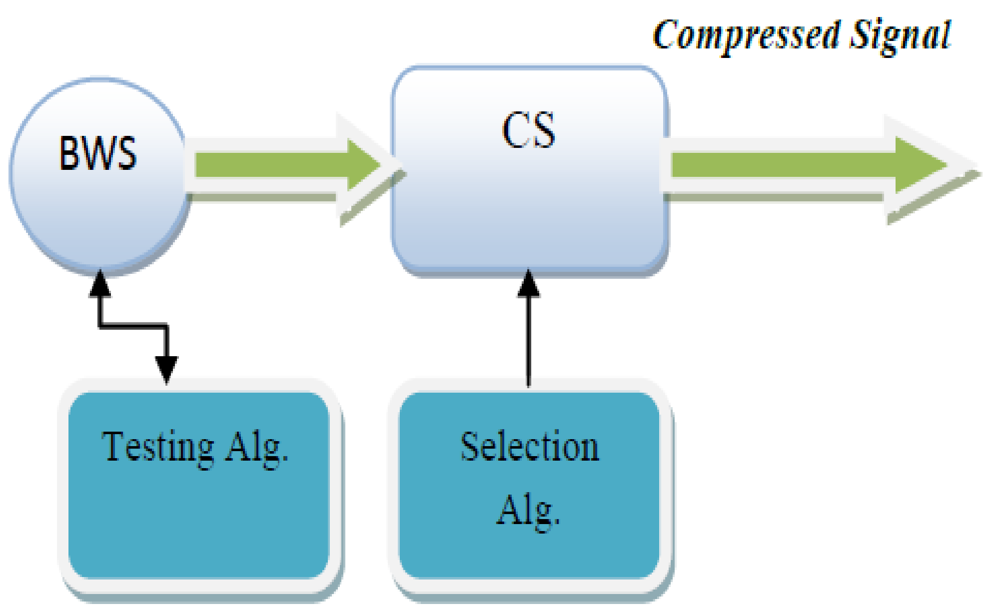


Fig.5.2: Combination of the proposed algorithm in the transmitter side

Figure 5.3 shows the combination of the Algorithms III and IV in the receiver side.

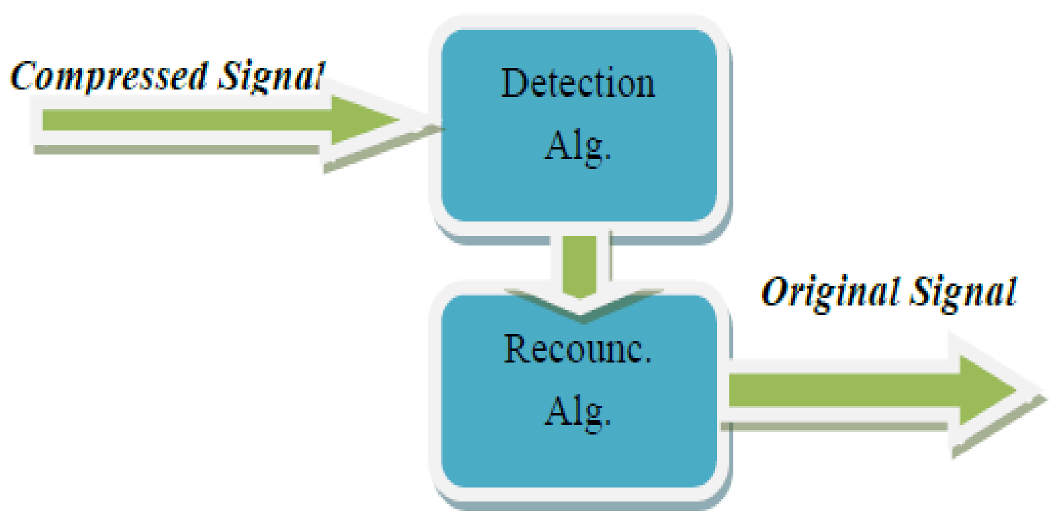


Fig.5.3: Combination of the proposed algorithms in receiver side

The main purpose of the testing algorithm is to increase the reliability and availability of BWSs in WBANs with more than one wireless sensor. Individual biomedical wireless node reliability must be measured to ensure the network is online and available. To achieve a high reliability and availability in WBSNs, a mechanism of testing for uncovering failing and failed BWSs is needed [128]. Therefore, testing in BWNs would help identify any BWNs that must be repaired or replaced before network availability suffers. Boundary Scan (BS), Hardware Built-In Self-Test (BIST) and SBST methods were introduced for testing wireless networks [129]. The BIST procedure needs embedded hardware test generators and test response analyzers to generate and apply the test patterns on-chip at the node under test. In other methods the BS applies test vectors to a wireless node, known as automatic testing equipment (ATE) by using an interface. Then, the test vectors execute with test responses being collected via wireless nodes. In order to detect faults in nodes, test responses are compared with the original test vector. They are also required to be physically interfaced for device-under-test (DUT). Regarding the application of WBNSs, it is often impossible to obtain physical access to the BWSs in order to perform functional testing on them [144]. There are some traditional methods to compress data, such as compression of Fully-Specified Test vectors (FST), compression of Incompletely-Specified Test vectors (IST), and compression and Compaction of Test Responses (CTR). The automated testing equipment is required for in-field testing of FST and IST methods [145, 146]. The automated testing equipment produces a *test cube* for each test vector executed. The CTR method needs a Linear-Feedback Shift-Register (LFSR) to reduce the size of the test response [147, 148].

Our new testing algorithm relies on collaboration between the Software-Based Self Test (SBST) approach and CS theory. The SBST approach offers a way to achieve high-quality testing in BWSs without using dedicated hardware [145]. It utilizes an existing MCU's vector to perform a self-test of all components such as the microcontroller unit, communication unit, sensing unit and power supply unit of BWSs. In order to uncover any BWSs faults, the SBST method produces various test sequences through all of the components of a wireless sensor. Then, it collects all of the test results and generates the compressed test vector. A compressed test vector of the combined test results is called a test *signature*. Then, the test signature is compared to a known- test vector stored at the MCU of the BWSs to detect any fault. The SBST method also sends test results of each BWS to the GW. The GW can generate an announcement to repair or replace failed BWSs before the availability and reliability of WBANs suffer. A general description of the SBST method can be seen in Figure 5.4. The SBST program can test a wireless node while it is running at full functional speed and also can determine if the hardware or software of the BWS has been tampered with by an intruder. The CS reduces the number of bits of the test-result. Fortunately, vectors of test response are vectors that are able to be compressed. In the other words, only a few selected bits of test responses are required in order to be properly processed. The CS theory states that a small number of test results bits contain sufficient information for approximate or exact testing. In our mind, the combination of SBST testing with CS can overcome some limits such as limited time of testing, limited reliability and limited processing capability in WBANs.

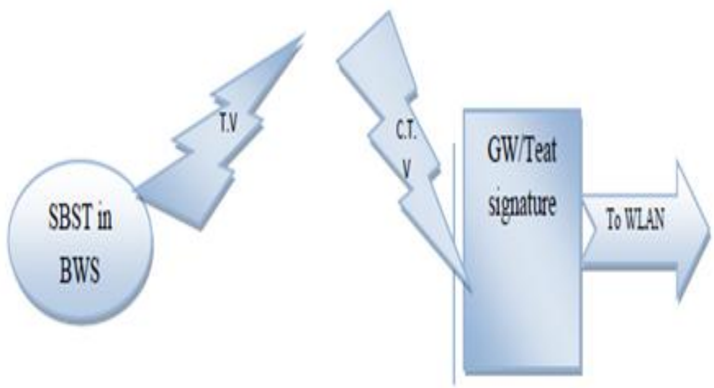


Fig.5.4: General Description of SBST method

The framework contains six major steps that are enumerated as follows:

Step1. The SBST generates random test vectors for BWS and collects the test results.
Step2. The test-result is compared with a result known in the BWS. The test-results are compressed, and the compressive test-result is sent to GW. If GW does not receive any test-result for each BWS, it is recorded as a failure of the BWS.
Step3. A different test vector is produced for each failed one using Test Driven Development (TDD) procedure
Step4: All compressed responses are collected by GW, and the test signature is generated.
Step5: The *test signature* is compared with known test data.
Step6: Any failure and fault is detected.
Step7. The GW generates a massage to WLAN to be repaired or to replace the failed BWS.

5.3. SBST based on CS theory

To achieve sufficient reliability and availability within wireless medical network, the periodic on-line testing approach is needed in order to pinpoint and repair or bypass the failed BWSs that might be physically unreachable. Recently, the use of a low-cost SBST algorithm based on CS theory is appealing to talented researchers as an effective alternative to the hardware BIST procedure to establish an on-line testing algorithm with high quality at-speed testing in normal operational mode with low-power and low-delay and without any power overhead. This algorithm uses existing processor resources with no hardware or performance overhead. The BWS nodes are usually battery powered and their replacement and recharge may not be feasible during their lifetime, especially in the implemented scenarios. Therefore, in addition to the test quality, energy consumption is a major concern in testing biomedical nodes. Thus, the current testing algorithms need to be developed further in order to achieve the following performances:

►Low-cost testing

►High speed and high quality testing

►Low-power and low sampling-rate test matrices

The SBST based on CS theory has a non-intrusive nature since it utilizes the existing on-chip programmable controller and the related instruction set for both test pattern generation and output data evaluation. The SBST based on CS theory renovates the utilization of Virtual Constraint Circuit (VCC) and consists of the following steps:

►At first, a set of functional patterns are used as the training tests.

►The collected results on the input and output boundaries of the Module Under Test (MUT) are monitored and recorded.

►After analyzing the results, the input and output VCC are generated for the MUT.

►The input and output VCC compress based on the simulated test patterns to reduce the test program's size and test application time.

►The compressed data are attached to the MUT to perform a compressed module VCC-MUT, and they rely on the extraction of functional constraints based on the instruction set architecture.

►A Test Pattern Generation (TPG) can now be applied to the compressed VCC-MUT data to produce tests for target faults in MUT.

►A dedicated Task Manage Node (TMN) or helper node remotely activates and then coordinates a self-testing of Node under Test (NUT).

►The NUT begins with CPU core self-testing, followed by a comprehensive test program for the rest of the testing period.

Figure 5.5 shows our SBST algorithm based on CS theory. GW sends the compressed SBST vectors to wireless nodes and collects the compressed test response. After recovery, GW can recognize a pass or fail condition. The SBST routines are located in the flash memory of the wireless node and can be updated a number of times during the lifetime of their applications.

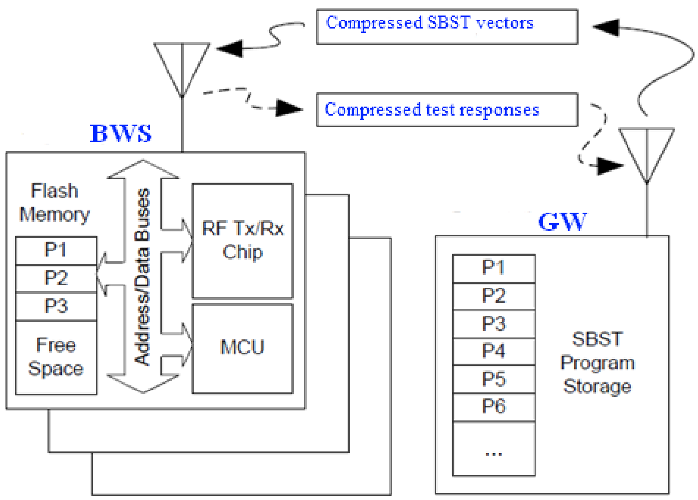


Fig.5.5: Structure of SBST Method with CS

Figure 5.6 shows SBST algorithm based on CS theory for a WBAN including *N* nodes.

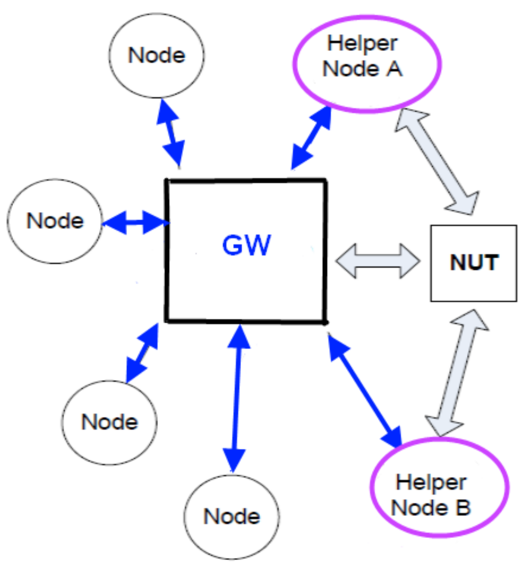


Fig.5.6: Structure of SBST Method for N nodes

Our algorithm for N biomedical wireless nodes includes the following steps:

►The NUT performs most of its testing through self-test but is also evaluated by neighboring wireless nodes.

►The GW generates the compressed SBST programs to the NUT.

►The on-board MCU decompresses the SBST programs and stores it in embedded flash memory, enabling the GW to remotely activate NUT self-testing.

►Data compression is the process of random measurements from the data set in order to represent the original test vectors and test responses with only a small number of random measurements of the test vectors.

►The NUT executes the embedded RAM and flash memory.

►A compressed signature is generated and sent back to the GW, where it is compared to a wireless node's known-reference signature.

►If a compressed signature is deemed correct, the test procedure is done; otherwise, an additional compressed test program is employed.

►For a more comprehensive evaluation, several wireless nodes neighboring of the NUT can be used to track a decline in communication efficiency.

►An additional compressed test program can be distributed to the NUT.

►The result is sent back to the GW, which tracks and analyses changes over time to recognize failing wireless nodes.

The benefits of applying CS theory to the SBST algorithm can be divided into three areas. The first area is to improve the quality of testing. As a result, uncovered and failed wireless nodes can be repaired or replaced before they affect the network's availability. The second area is to minimize the volume of data testing received by wireless nodes. Thirdly, it reduces wireless node consumption associated with the distribution of compressed test programs.

5.3.1. Network Simulator

To simulate the proposed algorithm Network Simulator 2 (NS-2) and Network Simulator 3 (NS-3) are employed on a WBAN including *N* wireless sensors. They operate on a discrete event simulation concept and are widely used in wireless networks, because they can easily simulate different parameters for wireless nodes. In addition, the simulation toolboxes provide dynamic memory management, which can add new entries and drop old entries. Additionally, the users can check the simulation steps without disrupting the program's operation. Moreover, they possess the following properties:

► Operate in object-oriented tools of C^{++}.

► Run on Linux/windows operation systems.

►Are open-source and provide online documents to allow the users to modify and improve the test parameters easily.

► Support a considerable range of protocols for wireless communication networks.

►Support toolboxes for testing purposes.

►Contain modules for numerous wireless network components, such as communications and control units.

The SBST method with CS theory is applied to multiple BWSs and can reduce the need for individual BWS testing. This testing scenario also can predict where BWSs have failing units such as batteries, RF communication, processing, and sensing units. It can increase network reliability and availability by predicting BWS failures through periodic testing. The SBST with CS leads to successful testing, thus achieving the reliability requirement. The proposed methodology is shown in Figure 5.7.

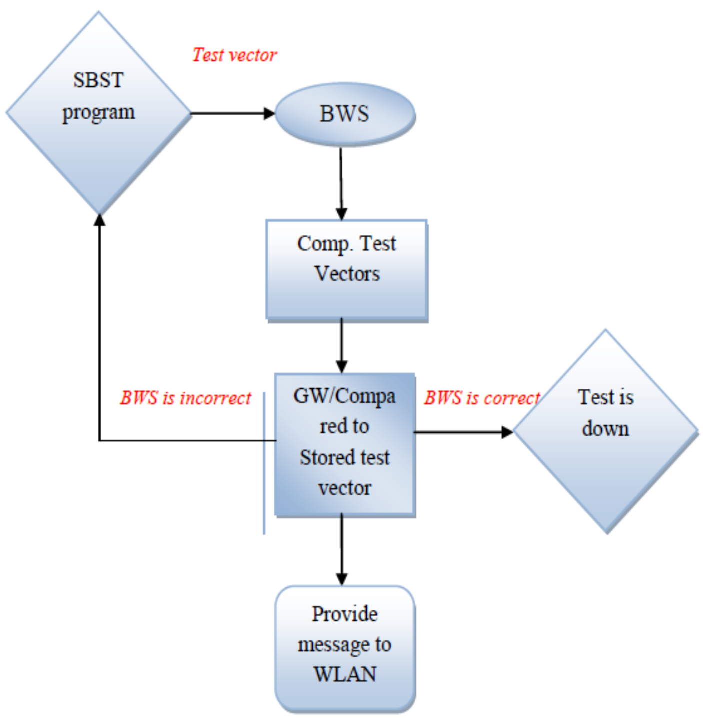


Fig.5.7: Flowchart of SBST Method with CS

Figure 5.8 shows a WBAN with *N* wireless sensors.

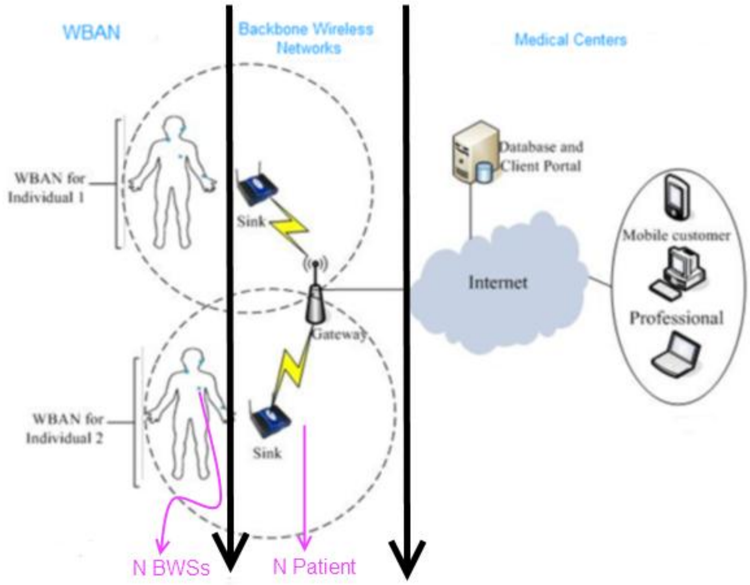


Fig.5.8: A WBAN with N BWSs

5.4. Simulation Results

In this section, the CS theory is applied to a particular WBAN with *N* wireless sensors for the monitoring of several patients at the same time as well as the monitoring of several vital signals of a patient. Our simulation shows that the sampling rate can be reduced to 25% without sacrificing performance; however, further decreasing the sampling rate will gradually reduce the performance until the 10% sampling rate is reached. The simulation results also confirm that CS theory can reduce power consumption to 30% without sacrificing performance. The simulation results were produced using the simulator developed in C++, and the following assumptions have been made:

►The numbers of BWNs are 100.

►BWNs are distributed according to a Gaussian or uniform arrangement in the area about 2000×2000 m.

►The power supply of each BWN has 15 joules for CU, PU and SU [150].

►The effective range for communication unit of each BWN is 20m.

►The simulation time is 825 seconds [151].

►Power consumption for the communication unit in sending mode is 550 mw and in receiving mode at GW is 25 mw.

►Each BWN consumes 9 mA in active mode and 5 μA in sleep mode.

►Bandwidth is 1.5 Mb/s .

►Each BWN has enough time to send its data to GW.

►Simulation packet size is 1500.

►Simulation interval is 150.

►The number of random measurements M is equal to the number of non-zero entries K .

►The data of BWNs are driven from a Uniform or Gaussian distribution between 1 and 200.

►Data of BWNs are generated at an interval of 2 seconds.

►The transmitted power is normalized to 1.

►PDF of random variable has Gaussian or Uniform distribution.

In this section, simulation results on the sampling-rate are presented first. Secondly, the simulation results of power consumption are illustrated.

5.4.1. Simulation on Sampling-rate

Figure 5.9 shows our simulation for the reduction of sampling rate in terms of Detection Probability (DP) with Gaussian distribution and different values for non-zero coefficients *K*.

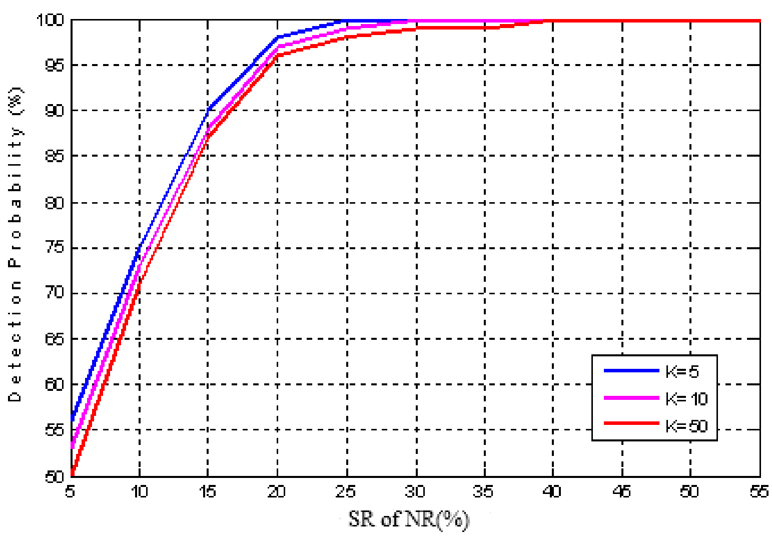


Fig.5.9: Sampling rate for K=5, K=10, K=50 with Gaussian distribution

Our result shows, that we can reduce the sampling rate to 25% without sacrificing the detection level. The following results are extracted:

►If the sampling rate is higher than 25%, the detection probability is almost 100%.

►The performance gradually decreases as the sampling rate decreases and *K* increases.

►The CR is increased when the number of random linear measurements is reduced; therefore, the detection probability depends on the value of CR, which is an important parameter in CS theory.

►By increasing the number of random linear measurements, the accuracy of detection events decreased. Table 5.1 shows our simulation of sampling rate with different values for *K*.

Table 5.1: Sampling rate reduction for different values of K

Number of non-zero entries	Sampling-rate	Probability of Detection
$K \leq 10$	Until 25%	100%
$10 \leq K \leq 25$	Until 30%	100%
$K \geq 25$	Until 35%	100%

In the non-CS scenario, a wireless node receiving *N-1* packets (each packet corresponding to a data sample from a wireless node) sends out *N* packets (the *N-1* received packets plus its own data sample). The base station, in particular, needs to receive all of the *N* packets. Table 5.2 compares our simulation results with non-CS network [151].

Table 5.2: Simulation results for non-CS network and CS network

Number of events	SR(Non-CS network)	SR(CS-based network)	Detection Probability
$K \leq 10$	100%	25%	100%
$10 < K \leq 25$	100%	30%	100%
$K > 25$	100%	35%	100%

Now the difference between CS and non-CS operation becomes clear: CS operation requires each node to send exactly *K* packets irrespective of what it has received. In non-CS networks, each wireless node needs to send N packets with $M \approx K \ll N$. In the CS scenario by compressing the data size is reduced and fewer bandwidths are required to transmit data due to compressing and therefore, less power is required to process and transmit data. Figure 5.10 shows our simulation with three values for $M \approx K$ with Uniform distribution.

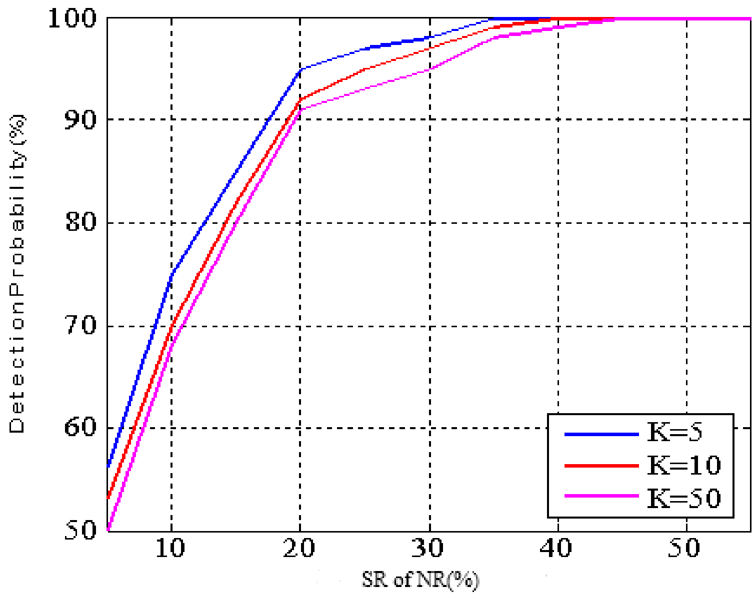


Fig.5.10: Simulation of sampling rate with uniform distribution

As the results demonstrate, the sampling rate can be reduced to 25-30% without sacrificing important performances because of applying the CS theory. Table 5.3 summarizes the results.

Table 5.3: Simulation sampling rate with uniform distribution

Number of events (k)	Sampling rate reduction (%)	Detection Probability (%)
$K \leq 10$	Until 25%	100%
$10 < K \leq 25$	Until 28%	100%
$K > 25$	Until 33%	100%

5.4.2. The Result of Power Consumption

Power consumption is the most important factor in determining the lifetime of a BWS to life of a wireless sensor because biomedical sensors are usually driven by a battery and have very low energy resources. This makes energy optimization more complicated in wireless medical networks because it involves not only reduction of energy consumed but also prolonging the life of medical network as much as possible. The lifetime of a biomedical node can be increased by reducing the sampling-rate load. The primary limiting factor for the lifetime of wireless nodes is the very low energy power supply, especially when they should implant into a body. Regarding the application of WBANs, it is impossible to get physical access in order to change or recharge the power supply. In the implemented cases, the BWSs will be set up in the hospital by medical staff and the localized sensors must be minimized to reduce power consumption. Therefore, each wireless node must be designed to manage its own power supply. A combination of CS theory to wireless medical networks is the optimal solution for achieving autonomous low-power networks. The lifetime of the power supply can be increased by drastically reducing the current in all the units of BWS. The CS scenario can reduce the number of bits of data through the whole of the network, and as a result the amount of current drawn from the power supply should be decreased. Consequently, the lifetime of the power supply is increased. Our simulation results show that CS theory as a new sampling method is beneficial in reducing the total of power consumption. Figure 5.11 shows the power consumption in terms of CR in the proposed network with 100 BWSs.

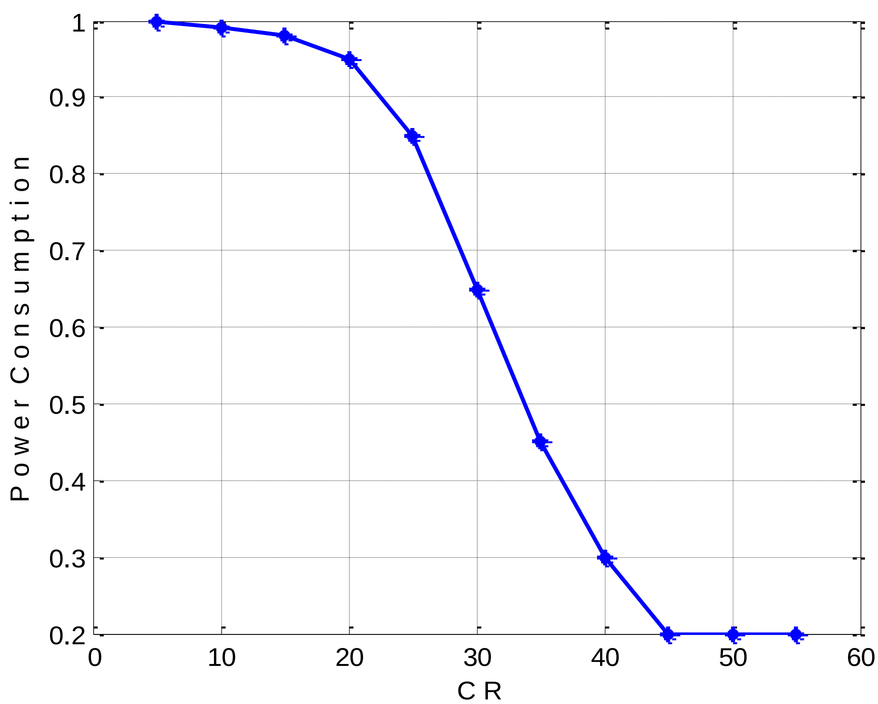


Fig.5.11: Simulation of power consumption

The simulation results are shown in Table 5.4 and compared with a non-CS network [152]. Our simulation shows that compressed sensing can reduce the number of data bits through the whole of network; consequently, it can increase sleep time for BWSs and minimize power consumption. Our results also show that WBANs can achieve a higher transmission, a low time delay, and a high probability of success of data transmission by employing the CS theory, because the addition of CS theory to WSNs is the optimal solution for achieving robust WBAN.

Table 5.4: Simulation of power consumption

Parameter	Without CS with N=100	With CS with M=10
Power consumption in CU	600 mw	110 mw
Power consumption in SU	200 mw	90 mw
Power consumption in PU	180 mw	80 mw
Time of sleep mode in WN	12 ms	108 ms

Figure 5.12 shows simulation results for power consumption in terms of CR for three biomedical signals with *N=1024, N=2048, N=3072* as a total of entries including zero and non-zero entries and with a Gaussian distribution for random measurements.

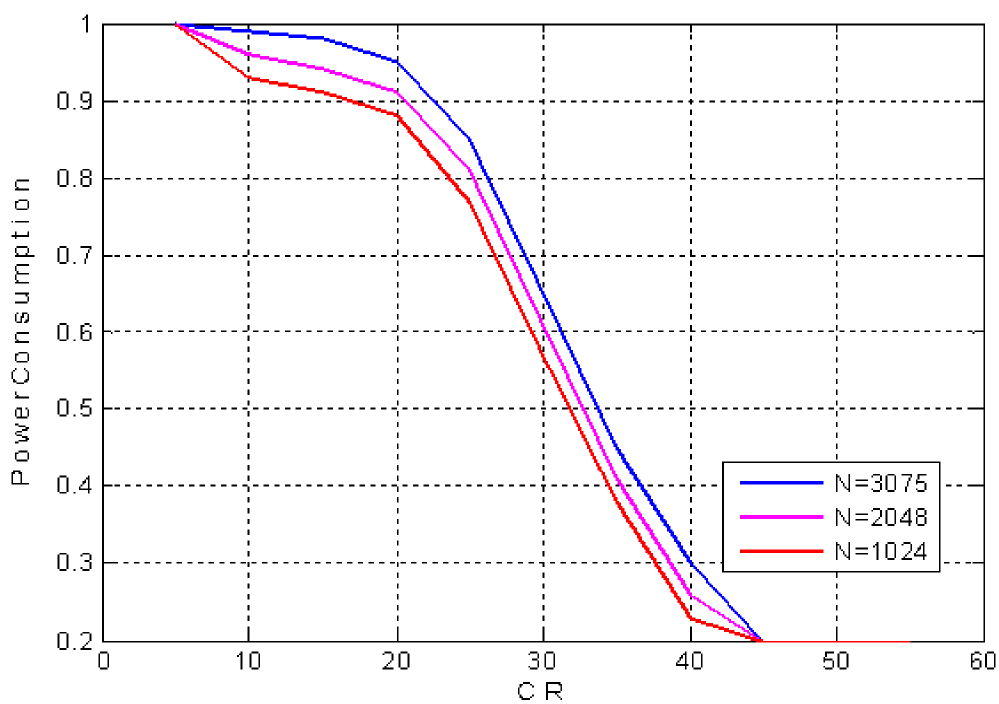


Fig.5.12: Simulation of power consumption

We have extracted the following results from our simulation:

► The CS theory can reduce power consumption in BWSs in order to increase the lifetime of the network.

►The power consumption decreases by increasing the value of CR.

►The CR increases by decreasing the number of random measurements.

Table 5.5 combines the results for SR and PC in a particular type of WSN.

Table 5.5: Final results for SR and PC

Number of random measurements (M)	Number of entries N=1024	Number of entries N=2048	Number of entries N=3072
100	CR=10.24 SR → 25% PC → 30%	CR=20.24 SR → 25% PC → 30%	CR=30.72 SR → 25% PC → 30%
200	CR=5.12 SR → 27% PC → 33%	CR=10.24 SR → 27% PC → 33%	CR=15.36 SR → 27% PC → 33%
300	CR=3.41 SR → 30% PC → 35%	CR=6.82 SR → 30% PC → 35%	CR=10.24 SR → 30% PC → 35%
400	CR=2.04 SR → 33% PC → 37%	CR=5.10 SR → 33% PC → 37%	CR=7.68 SR → 33% PC → 37%

5.4.3. The Result of SBST based on CS theory

The simulation results show that by applying CS theory to the SBST algorithm, the volume of data received by the node directly as well as by GW can be minimized. This fact leads to a reduction in wireless node energy consumption. The simulation resulted in enhanced probability for receiving the packets at GW; this is the key criterion to increase the network's availability and reliability. Figure 5.13 illustrates detection probability in terms of distance between the wireless node and GW for SBST algorithm, in the cases with and without CS theory. Figure 5.14 demonstrates the retry limit parameter for the particular WBAN including *N* wireless sensors in terms of SBST packets per second. The SBST with CS theory shows an increment of number of retry limits. This ability can allow the network to achieve better reliability and availability. Finally, Figure 5.15 shows the number of SBST packets in terms of Transmission Control Protocol (TCP) flows in the cases with CS and without CS theory. The results emphasize that satisfying quality in the number of SBST packets can be achieved when CS theory is applied to the SBST algorithm.

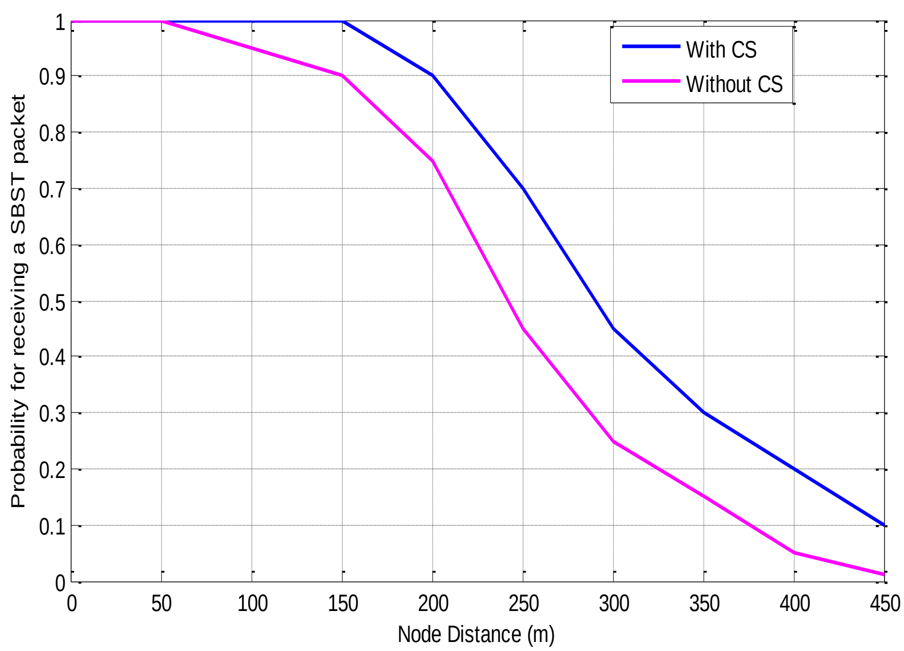


Fig. 5.13: Detection probability at GW for SBST based on CS

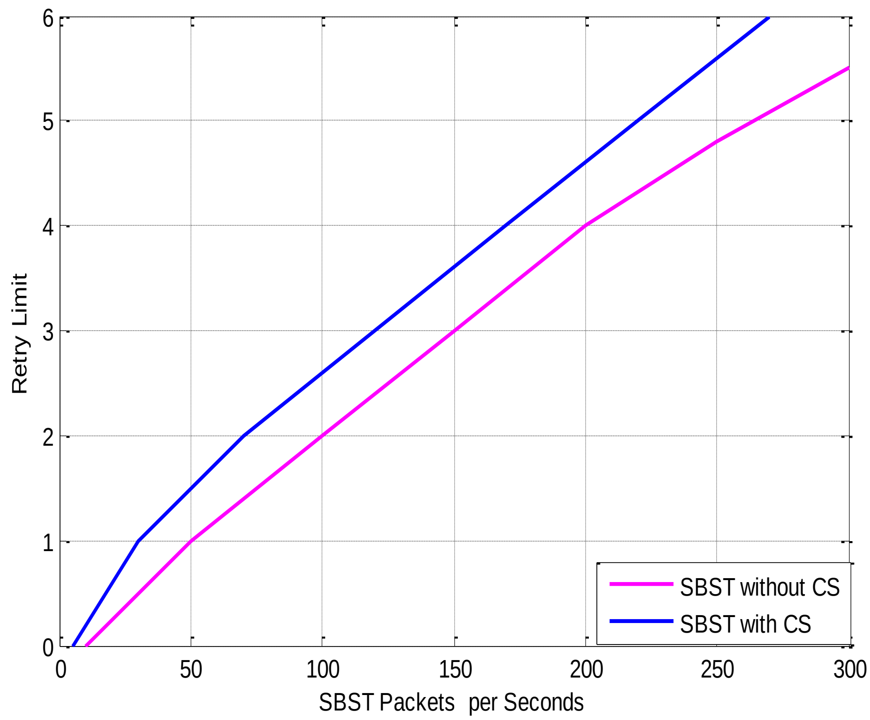


Fig. 5.14: Retry limit in terms of SBST packets

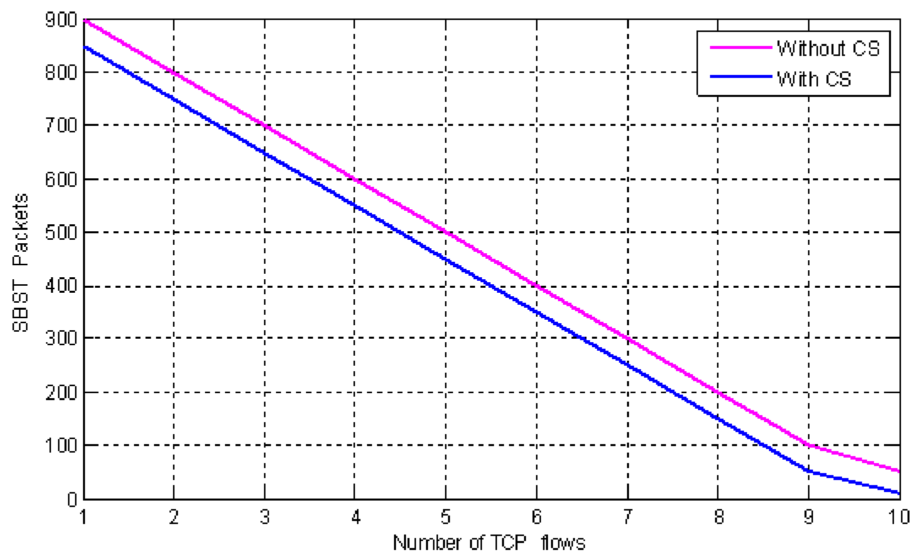


Fig. 5.15: SBST packets in terms of TCP flows

5.5. Chapter Summary

The research in WBANs is one area that has not yet experienced the advantages that CS theory can bring, such as decreasing power consumption, decreasing cost and size, and increasing processing capability. This chapter described how CS theory can be applied to a particular WBAN with N wireless sensors in order to minimize cost, power, and delay. It discussed two key features, a new sampling method for WBANs, and a new reconstruction method to recover the original information. This chapter emphasized that CS theory is the optimal solution for increasing the lifetime of wireless nodes. We have shown that CS holds promising improvements to overcome limiting characteristics, such as power consumption, lifetime, traffic and time delay. We have discussed how CS can reduce the number of bits of information in BWSs. In this chapter, we concluded by proving that the sampling-rate can reduce to 30% and power consumption to 40% without sacrificing the performance that defines the probability of detection.

5.6. Plan for next Chapter

In the next chapter, we present a new channel model based on CS theory for transferring the collected and compressed biomedical signals from the human body to GW and then to AP. The fundamental objective of this model is to minimize the path loss as well as the number of arrival paths in the receiver side. Figure 5.16 shows the plan for the next chapter. Based on this figure, the following concepts are presented in the next chapter:

► Define different types of channels for WBANs.
► Present new channel model for transmitting the compressed biomedical signals.
► Find the mathematical rules for received signal.
► Verify the proposed channel model.
► Calculate the channel features based on the proposed model.
► Simulate the channel features based on the proposed model.
► Compare the channel features in non-CS and CS scenarios.

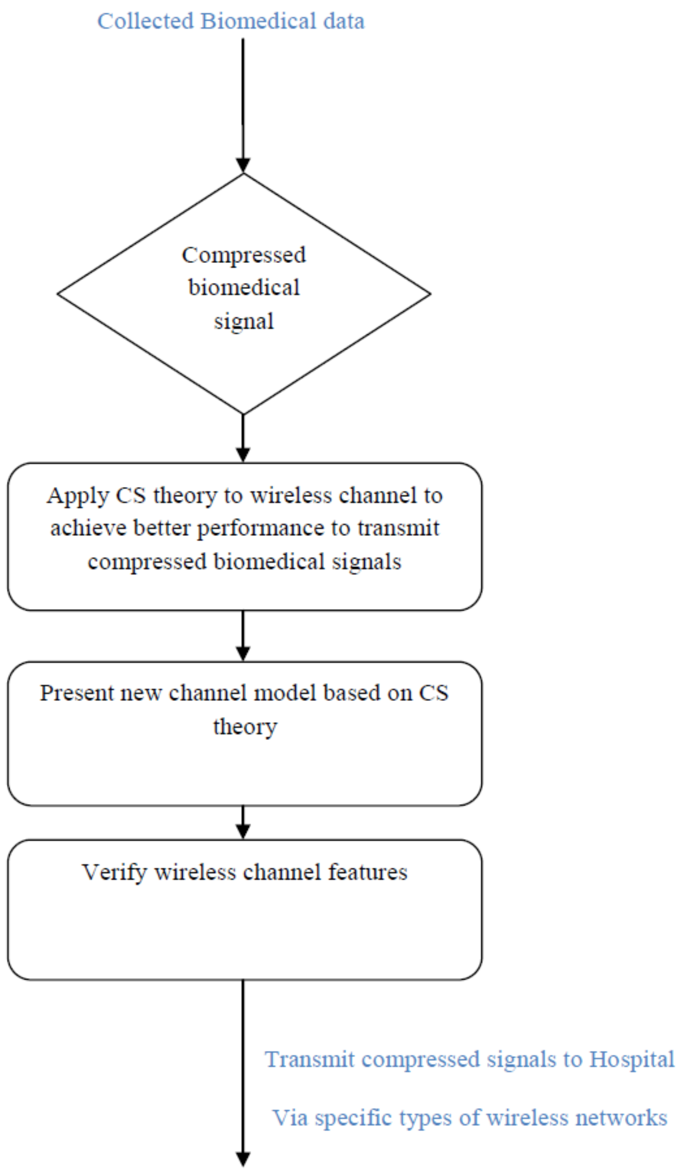


Fig.5.16: Plan for next Chapter

Chapter 6

Multipath Fading Channels based on CS theory

6.1. Motivation

To increase the reliability of WBANs, the power consumption and sampling-rate should be minimized in the MFCs between BWSs and GWs or APs. That is why an improvement of Multipath Fading Channels (MFCs) as well as a low sampling-rate channel model is inevitably required for WBANs in order to expand WBANs to important applications such as EH and MH. With this in mind, CS theory, as a new sampling procedure, is applied to MFCs. By employing CS theory to MFCs, the PL, the number of arrival paths, and BER at GW could be minimized. These are the main reasons for CS theory being a potential candidate for MFCs. The MFCs based on CS theory also serve the goal of reducing healthcare costs in WBANs because they can service several patients simultaneously. To apply CS to WBANs, the improvement of MFCs as well as a statistical channel model based on CS theory for the on-body to on-body scenario is considered. The main motivation of this chapter is to define new channel model based on CS theory for wireless healthcare systems. This chapter investigates a statistical channel mode for MFCs based on CS theory. Figure 6.1 shows our plan for this chapter.

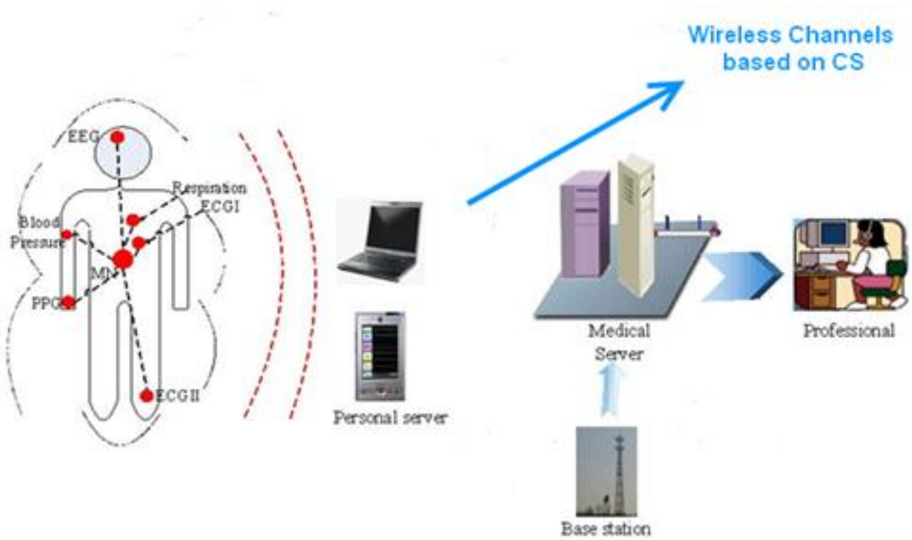


Fig.6.1: Plan for this Chapter

Our simulation results attained a 20% reduction for PL and 10% for BER at GW. The simulation results also confirm that the signal amplitude at GW increases by 25%, which will result in an increase in the distance between transmitter and receiver sensors. The structure of this chapter is organized as follows: Section 2 shares how CS theory contributes to a new aspect of wireless sensor networks; and Section 3 investigates MFCs in WBANs. Section 4 offers our model for MFCs. The simulation results, including results on PL, BER, signal amplitude, sampling rate, and power consumption, are presented in Section 5. The chapter summary is drawn in Section 6.

6.2. Contribution

The fundamental contribution of this chapter is to apply CS theory to wireless channels in WBANs. The new channel model is presented based on CS theory for WBANs. The main reason for this model is to minimize the PL and maximize received signal amplitude at the receiver. To communicate biomedical signals in the WBANs, propagation paths can experience fading for different reasons, such as energy absorption, reflections from the body, diffraction from other bodies, shadowing by body, body postures, and multipath due to the environment around the body. We illustrate that log-normal and Ricean distributions are suitable for the MFCs in WBANs. The power usage can be minimized by optimizing the features of MFCs, such as the number of arrival paths in WBANs. That is why an improvement of MFCs as well as a simple and generic channel model will be inevitably required. With this in mind, CS theory, as a new sampling procedure, is employed for MFCs. To apply CS to WBANs, an improving of MFCs as well as a statistical channel model based on CS theory for the on-body to on-body scenario is presented. This contribution investigates a statistical channel mode for MFCs based on CS theory for WBANs. We present a statistical channel model for on-body to on-body scenario, considering specific requirements. Our dedicated channel model uses CS theory in order to eliminate interference issues, while applying low sampling rate procedure for WBANs. Our model consists of the following steps:

Step1: Calculate the received signal at GW in terms of overall attenuation and propagation.

Step2: Investigate the impulse response for the MFCs.

Step 3: Propose the baseband equivalent impulse response for MFCs.

Step4: Employ Log-normal and Ricean distribution for Small-Scale Fading (SSF) and Large-Scale Fading (LSF).

Step5: Calculate the average PL based on CS theory.

Step6: Simulate the PL and the received signal amplitude at GW.

Step7: Validate to minimize PL and maximize received signal amplitude at GW.

6.3. Channels in WBANs

In the WBANs, BWSs have the capacity for wireless communication and can sense biological signals from the human body. Figure 6.2 shows system architecture of a WBAN, including BWSs, GWs, and APs.

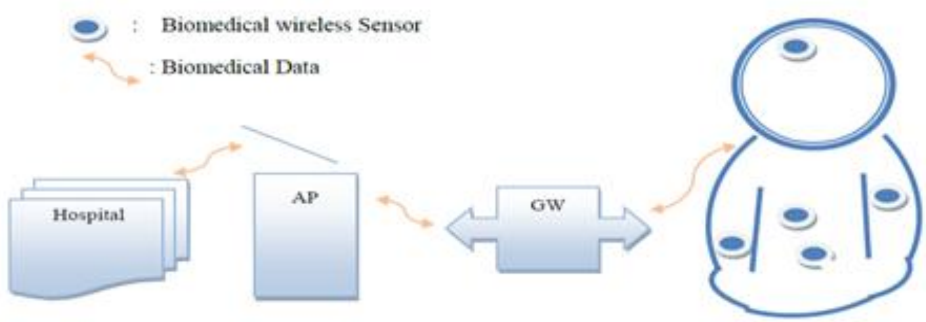


Fig.6.2: Specific architecture for WBANs

Based on Fig. 6.2, the channel behavior can be divided into three links:

►The channel model between the wireless sensors in/on the human body,

►The channel model from the wireless sensors in/on the human body to the GW,

►The channel model from the GW to access points at home, in the hospital, in the van, and in a helicopter. The GW collects all biomedical data from wireless sensors. The collected data are then transmitted to APs using specific types of wireless networks such as WPAN or WLAN for diagnostic and therapeutic purposes. Some protocols are given for supported communication of biomedical data between sensors with APs [125]. The IEEE802.11 protocol supports WLANs for hospital and home cases; the IEEE802.16 can be employed for the ambulance helicopter; and the IEEE802.11P is proposed for the ambulance van case [126]. Interaction with the user or other persons is usually handled by a Personal Digital Assistant (PDA), Central Control Unit (CCU), smart phone, or GW. The WBAN consists of the following two main parts: multiple Wireless Body Sensor Units (WBSUs) and a Wireless Body Center Unit (WBCU) [127]. The WBSUs perform vital medical data acquisition, data processing, data transmission as well as providing some basic user feedback. In addition, the WBCU links multiple sensor units and performs data collection, data compression and event management. Afterwards, the physiological information is transmitted wirelessly to the medical centers. The IEEE802.15.6 supports WBANs for low power wireless nodes and for operation in or around the human body to serve a variety of applications [128]. This system standard also employs a frequency-hopping multiple access scheme to combat interference and fading [129]. To investigate the behavior of MFCs in WBANs, this protocol is categorized into four scenarios: on-body to on-body, on-body to around-body, in-body to on-body, and in-body to in-body [130]. We have focused on the on-body to on-body scenario in this chapter since it includes the applications of WBANs in the CHMSs.

6.4. Multipath Fading Channels

To communicate biomedical signals in the WBANs, propagation paths can experience fading for different reasons, such as energy absorption, reflections from the body, diffraction from other bodies, shadowing by body, body postures, and multipath due to the environment around the body. We illustrate that log-normal and Ricean distributions are suitable for the MFCs in WBANs. Regarding the applications of Health Monitoring Systems (HMSs), fading in WBANs can be categorized into the two areas of SSF and LSF [131]. The SSF in WBANs refers to the rapid changes of amplitude and phase of the received biomedical signals in the Gateway for a given short time period. They are divided into flat fading and frequency selective fading. To reduce the effect of SSF due to small changes in body position, it is possible to average the attenuation between each antenna position on the body and each antenna location in the room. The SSF or the amplitude distribution measured near the body is different from the other environments. Regarding the number of multipath components from any diffraction around the human body, the log-normal distribution shows a much better fit for SSF than the traditional models. Furthermore, only a weak correlation between the first and second paths is found [132]. This means that all paths are statistically independent. That is why we have the number of independent multipath that can be averaged to detect biomedical signals. It can be used as a benchmark to access the performance board of various WBANs. The LSF in WBANs refers to the fading due to motion over large areas such as homes, offices, or medical environments. By decreasing the distance between antenna positions on the body and external wireless nodes, which are allocated in home and office, the WBANs are advancing towards EH.

6.5. Proposed Model

As far as we know, the existing models for MFCs are inadequate for WBANs. So, it is important to investigate the characteristics of WSs when propagated in an environment around the human body. We present a new statistical channel model for the on-body to on-body scenario, considering its unique requirements. Our dedicated channel model is based on CS theory in order to eliminate interference issues, while applying the low sampling rate procedure to WBANs. Figure 6.3 shows input/output for channels of WBANs. The wireless sensors generate the input signal, and GW in the WBANs receives the biomedical signals wirelessly.

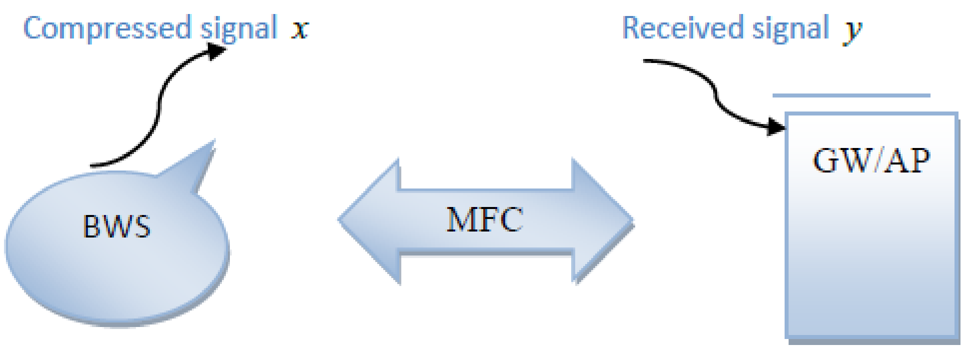


Fig. 6.3: Input /Output for channels of WBANs

The received biomedical signal in GW can be written as:

$$y(t)=\sum_{i=1}^{L}a_i(f,t)x(t-\tau_i(f,t)) \quad . \tag{6.1}$$

where $a_i(f,t)$ and $\tau_i(f,t)$ are, respectively, the overall attenuation and propagation delay at time t from the transmitter's wireless sensor to the receiver's wireless sensor at GW, L is the number of arrived paths, $x(t)$ is the output signal of WS, and $y(t)$ is the input signal for GW. Fortunately, only a weak correlation between the arrival paths is noticed. Thus at GW we have L as the number of independent multipaths. Further in the simulation part, we assume that $a_i(f,t)$ and $\tau_i(f,t)$ do not depend on the frequency f in order to use a principle of superposition. Therefore, the received biomedical signal at GW is shown as:

$$y(t)=\sum_{i=1}^{L}a_i(t)x(t-\tau_i(t)) \quad . \tag{6.2}$$

The impulse response for the MFCs can be expressed as:

$$h(\tau,t)=\sum_{i=1}^{L} a_i(t)\delta(\tau-\tau_i(t)) \quad . \tag{6.3}$$

This expression is simple and practical. The effect of patient's movements, arbitrarily moving reflectors and absorbers, and all of the complexities of solving Maxwell's equations through the human body, finally reduce to an input/output relation between the transmitter on/in the body and the receiver in the GW. This interaction is simply represented as the impulse response of a linear-varying channel behavior. Our simulation results show this ability can allow MFCs to achieve superior performance compared to most existing models. In the special biomedical case where the transmitter sensor, receiver sensor and the biomedical environment are all stationary, the attenuation and propagation delay in GW does not depend on time t; and we have the usual linear time-invariant MFC with an impulse response shown as:

$$h(\tau)=\sum_{i=1}^{L} a_i\delta(\tau-\tau_i) \quad . \tag{6.4}$$

At the transmitter's wireless node, the last step of the operation is to "up-convert" the biomedical signal to the carrier frequency and transmits it via the antenna. Similarly, the first step at the receiver wireless sensor is to "down-convert" the RF biomedical signal before further processing it. Thus from an MFC design point of view, it is most useful to have a baseband equivalent representation of the MFC systems. The baseband equivalent impulse response for MFCs is expressed as [134]:

$$h_b(\tau,t)=\sum_{i=1}^{L} a_i^b\delta(\tau-\tau_i(t)) \quad . \tag{6.5}$$

Where a_i^b is found from the following equation [134]:

$$a_i^b=a_i(t)\exp(-j2\pi f_c\tau_i(t)) \quad . \tag{6.6}$$

Finally, the base-band output in GW is the sum, over each patch, of the delayed replicas of the base-band of the input signal and is found as [135]:

$$y_b(t)=\sum_{i=1}^{L} a_i^b(t)x_b(t-\tau_i(t)) \quad . \tag{6.7}$$

where x_b is the base-band equivalent representation of $x(t)$ which is generated by the wireless sensor on the body. Table 6.1 exhibits important features for received signal at GWs or APs in the on-body to on-body scenario. Biomedical measurements for this scenario are obtained for the frequency range of UWB [136].

Table6.1: Parameters of Received Signal at GWs/APs

Position	Reduction	Loss(db)	Received signal (mV)
The head	3.3%	-0.15	6.9
The wrist	2.9%	-0.12	4.8
The thigh	1.8%	-0.08	3
The ankle	2.8%	-0.12	1.9
The ear	1.5%	-0.07	1.5

6.5.1. Path Loss

The human body in WBANs consists of different dielectric constants, thickness, and characteristic impedance; therefore, it is not an ideal environment for wireless communication. On the other hand, the absorption of the human body effects varies in magnitude with both the frequency of the applied field and the characteristics of the tissue. That is why the PL for WBAN is both distance and frequency-dependent [137]. The SSF and LSF follow a Log-normal and Ricean distribution. Due to the wide frequency band of UWB in WBANs, the PL is a function of frequency as well as of distance and can be presented by a product of the terms as follows [138]:

$$PL(f,d) = PL(f)PL(d) \quad . \tag{6.8}$$

The frequency dependence of the PL is described as:

$$(f^{(-k)})^2 \propto PL(f) \ , \tag{6.9}$$

where k denotes the frequency dependence factor determined by the configurations of the WNs. The distance dependence of the PL in dB is expressed as [139]:

$$PL(d) = PL_0 + 10n\log_{10}(d/d_0) + X_\delta \ , \tag{6.10}$$

where $P_L(d)_0$ is the path loss at the reference distance d_0, n is the PL exponent, and X_δ is a shadow fading, which has a Gaussian-distributed random variable. In the simulation part, our results confirm that PL is reduced in MFCs using CS theory by decreasing X_δ. The Average Path Loss (APL) can be expressed as [140]:

$$PL_{(average)}(d) = 10\log_{10}\left[\sum_{j=1}^{M}\sum_{I=1}^{N} 1/MN\left|H\sum_{i}^{d}(f_i)^2\right|\right] , \tag{6.11}$$

where H_i^d is the jth channel transfer function at a frequency *f* in a distance *d*, *M* is the number of channel transfer functions for the distance *d*, and *N* is the number of frequency components in the CTFs. As CS theory is employed, it is evident that as *M* and *N* decrease the APL is reduced to improve signal detection at GW. On the other hand, the Average Path Gain (APG) at a frequency *f* and position *p* at GW is obtained by [141]:

$$P_G^P(f) = \sum_{i=1}^{N} 1/N \left| H_i^d(f_i)^2 \right| \quad . \tag{6.12}$$

By employing CS theory, APG increases by reducing the number of CTFs. Our simulation results show that this ability allows it to achieve better power performance for the received signal at GW. The PL depends on the distance between the transmitter wireless node on the body and receiver wireless node at the GW with respect to the path loss exponents. The PL can be simplified as:

$$PL(d)[dB] = a\log_{10}(d) + b + N \ , \tag{6.13}$$

where *a*, *b* are coefficients of linear fitting, d is distance between transmitter and receiver, and *N* is a normally distributed variable with zero mean and variance ∂_n. Table 6.2 shows these parameters for 400 MHz [142].

Table 6.2: Parameters for path loss in terms of the distance

Parameters for PL /d	F=400MHz
a	3.2
b	35
∂_n	4.7

In our simulation, PL is divided into the two domains of PL for SSF and PL for LSF. The SSF is represented by a Ricean distribution with K factor that increases by reducing the PL. The K factor in SSF can be found as:

$$K_{dB} = K_0 - m_K PL_{dB} + \partial_K n_K \, , \tag{6.14}$$

where K_0 is the Ricean factor, m_K is the slope of the linear correlation between PL and Ricean distribution factor, ∂_n is the log-normal variance, and n_K is zero mean and unit variance Gaussian random variable. The PL in dB for LSF is described as:

$$PL_{(dB)} = PL_0 + 10\Gamma \log_{10}(d / d_0) + X_{\partial}, \quad (6.15)$$

Where d_0 is the reference distance, Γ is the slope in units of dB/m, and X_{∂} is a large scale shadowing, which has a Gaussian distribution with standard deviation ∂, and PL_0 is the PL at the reference distances. Our simulation results further confirm that based on CS theory PL for LSF is reduced by decreasing X_{∂}. Another important parameter of a MFC is the multipath delay spread T_d, which is defined in propagation time between the longest and shortest path, counting only the path with significant energy. The multipath delay spread is expressed as:

$$T_d = \max_{i,j} \left| \tau_i(t) - \tau_j(t) \right|, \quad (6.16)$$

where τ_i and τ_j are propagation delay for path i and j respectively. The maximum detectable delay $\tau_{\max}$ of MFCs can be found [143]:

$$\tau_{\max} = (M - 1) / B, \quad (6.17)$$

where B is bandwidth and M is frequency per sweep and is constant.

6.6. Simulation Results

In this section, the features of an MFC such as PL, PDP, and detectable delay are simulated. The following assumptions were made for the simulation:

►The MFCs' parameters were extracted from measured Channel Transfer Functions (CTFs) for various frequency bands permissible for UWB between 400 MHz to 11 GHz.

►The MFCs in this band cover the ISI band as well as whole frequency bands of the UWB.

►The biomedical data was adopted from MIT-BIH database.

►The Finite Difference Time Domain (FDTD) procedure was used to simulate MFCs in UWB close to the human body.

►The log-normal distribution was used to investigate SSF of MFCs.

►The exponential distribution was used for arrival paths at Gateway.

►The Gamma distribution was used for average fading duration.

►The permissible parameters were adopted from IEEE802.15.3, IEEE802.15.5, and IEEE802.16e protocols that support low power communication in WBANs.

►The MFCs characteristics were simulated in both time and frequency domains.

►To simulate the MFCs, the channel links in WBANs are divided into these two main parts: the channel between the WNs on/in the body and the GW and the channel between the GW to the AP.

►The following equation was used for the impulse response function of MFCs for both SSL and SSF scenarios:

$$h(t) = \sum_{l=0}^{L} a_l \exp(j\phi_l)\delta(t - t_l), \tag{6.18}$$

where a_l is path amplitude, ϕ_l is phase, and t_l is path arrival time for l -th path.

►Based on Table 6.2, to simulate PL in SSF the following equation was used:

$$PL(d)[dB] = 3.2\log_{10}(d) + 35 + N, \tag{6.19}$$

where N is normally distributed variable with zero mean and variance 4.7 for 400 MHz and d is the distance between transmitter and receiver wireless nodes.

►The PL in LSF was based on the following equation:

$$PL(d) = PL_0 + 10\Gamma\log_{10}(d/10cm) + X_\partial, \tag{6.20}$$

where $\Gamma = 1dB/m$ and X_∂ is a large scale fading that has a Gaussian distribution with zero mean and $\partial = 1$.

6.6.1. Simulation Results on PL

The important steps in the improvement of performance of MFCs are to:

► Minimize PL.

► Maximize received signal amplitude at GW.

Utilizing these advantages, the WBANs are advancing towards EH, which gives patients greater physical mobility because they are no longer compelled to stay in the hospital. By this convenient means, elderly people can keep track of their healthcare conditions without frequent visits to the doctor’s office. By employing CS theory, the simulation results show PL can be reduced by 20% and the received signal amplitude at GW can be increased by 25%. The Gamma distribution is the best fit to simulate fading duration in MFCs. Figure 6.4 compares the fading duration in terms of Probability Density Function (PDF) at GW for SSF in CS and non-CS scenarios. As can be seen, the duration of PDF in the CS scenario is increased which results in an incremental increase in the probability of detecting signals at GW. Figure 6.5 compares biomedical signal amplitude in (dB) in terms of frequency in CS and non-CS scenarios. Based on

Fig, 6.4, simulation results show an incremental increase in the signal amplitude at GW by applying CS theory.

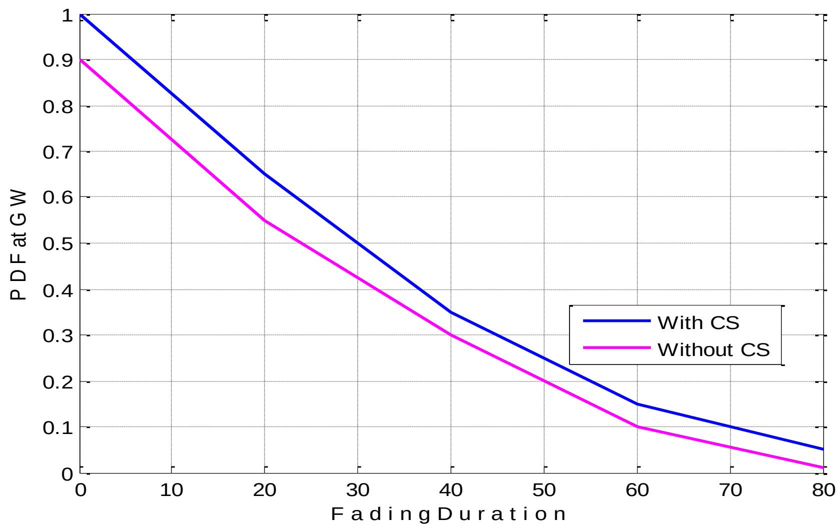


Fig.6.4: Fading duration for SSF

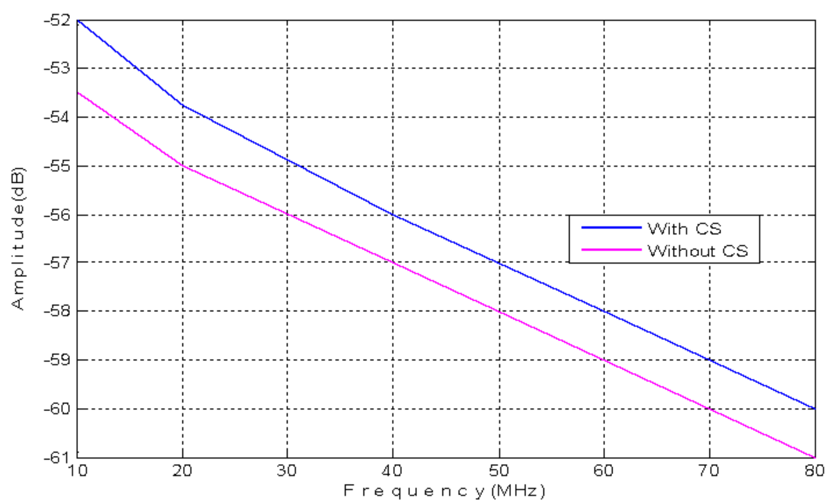


Fig. 6.5: Received signal amplitude at GW/ Frequency

Figure 6.6 gives a comparative work on PL in (dB) of LSF in CS and non-CS theory. It is evident that the distance between transmitter and receiver wireless nodes can be increased by applying CS theory to MFCs.

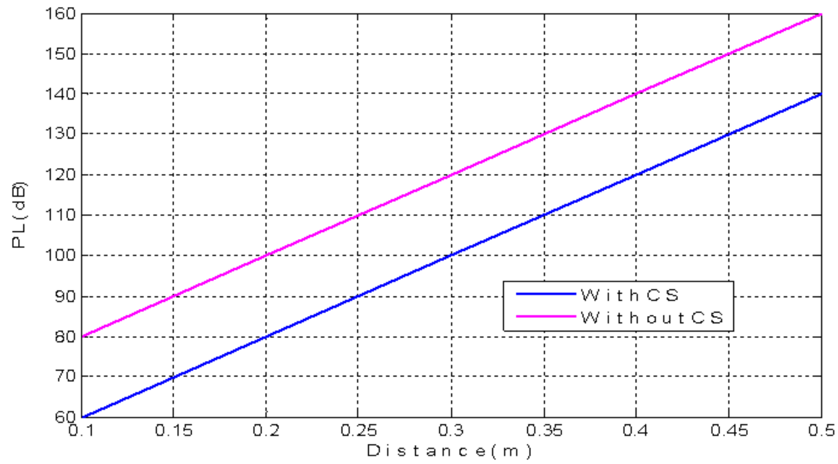


Fig. 6.6: Path loss for LSF

Figure 6.7 provides another comparative work concerning biomedical signal magnitude at GW in terms of PL for LSF in CS and non-CS scenarios. It illustrates that biomedical signal magnitude at GW is increased by employing CS theory.

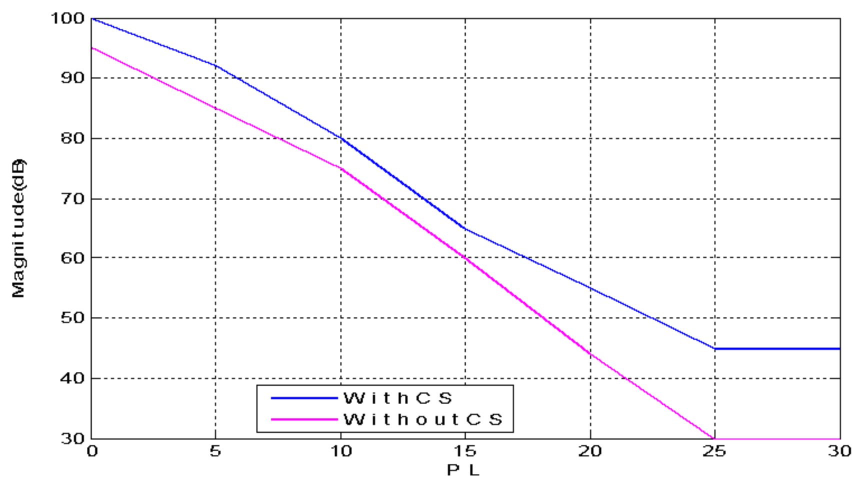


Fig.6.7: Biomedical signal amplitude for LSF

In summary, the simulation results show signal amplitude at GW can be increased by 25% and PL can be decreased by 20%. An important aspect of the simulation results is the increased distance between transmitter and receiver wireless nodes by 30%. This ability allows the expansion of WBANs to applications like EH. The simulation results illustrate the probability of signal detection at GW increases by 20% through using CS scenario. Figure 6.8 provides a comparative work about detection probability of biomedical signal at GW using CS and non-CS theory. Finally, Figure 6.9 provides another comparative work regarding biomedical signal magnitude at GW in terms of PL for SSF in CS and non-CS scenarios. It illustrates that biomedical signal magnitude grows at GW is increased by employing CS theory.

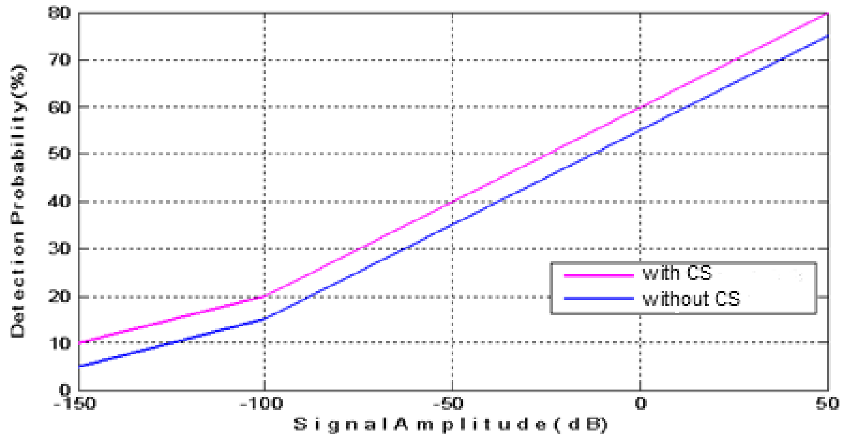


Fig.6.8: Probability of signal detection at GW

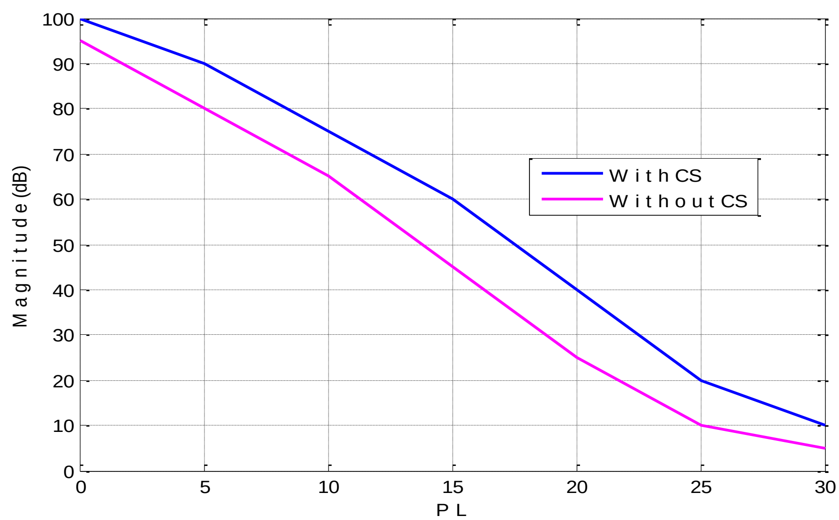


Fig.6.9: Biomedical signal amplitude for SSF

Table 6.3 summarizes the results on PL, signal amplitude at receiver, and distance between transmitter and receiver wireless nodes by employing CS theory.

Table 6.3: The results on PL, signal amplitude at receiver, and distance

PL	Signal amplitude	Distance
↓ **20%**	↑ 25%	↑ 30%

6.6.2. Simulation Results on BER

The reliability of a WBAN is directly related to the packet loss probability and packet transmission delay. The simulation results show that CS can help in reducing the effective BER by using an adaptive sampling procedure to suit the transmission channel conditions. The result is an increase in higher packet transmission. Higher packet transmission success probability reduces the packet delay and conserves the power budget of a WBAN. The power budget could be optimized by increasing successful packet transmission probability. The simulation results illustrate the probability of signal detection at GW increases by 20% when using CS scenario, and BER also decreases by 10% at GWs or APs. Figure 6.10 compares the Bit Error Rate (BER) of received signals at GW.

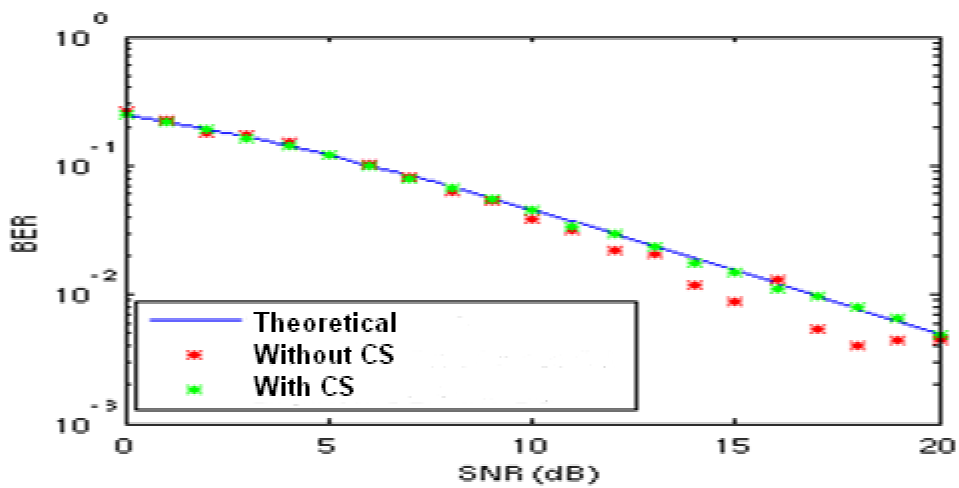


Fig.6.10: BER with CS and non-CS

The simulation results indicate that the acceptable level of probability for the signal detection and BER can be achieved when CS is employed in MFCs.

6.7. Chapter Summary

The WBANs are expected to provide the breakthrough technology in healthcare areas, such as electronic health, home care, telemedicine, and physical rehabilitation. To expand WBANs to these applications, the power consumption and sampling rate should be minimized. On the other hand, WBANs are one area that has not yet experimented with the benefits that CS theory might provide. To investigate the benefits of CS to WBANs, an improvement of the features of MFCs as well as a generic channel model is required. In this chapter, we have explored the advantage of applying the CS theory to MFCs, such as minimizing PL and BER. We first described how to employ the CS theory in MFCs for achieving a universal model for MFCs. Second, we formulated the conditions for applying the CS theory to MFCs. Our simulation results show PL can be reduced by 25% and BER by 10% when employing CS theory in MFCs. The simulation results also indicate that good quality MFCs can be achieved when signal amplitude at GW increases by 25% and the distance between transmitter and receiver wireless sensor increases by 30%. Finally, we applied the result of MFCs with CS theory to a particular ECG signal. Advanced WBANs based on CS theory would be able to deliver healthcare not only to patients in hospitals and medical centers but also in their homes and workplaces; thus, offering cost saving and improving the quality of life. As an important result of these networks, patients gain more mobility and comfort with medical equipment. Further applications of WBANs with CS theory open the door to numerous possibilities to improve the quality of collected medical data in order to make the medical decisions for diagnostic and therapeutic purposes.

6.8. Plan for next Chapter

In the last chapter, the results from applying CS theory to WBANs are concluded.

Chapter 7

Conclusions and Future Work

7.1. Conclusions

The main conclusion of this dissertation is that advanced WBANs based on CS will be able to deliver healthcare not only to patients in hospital and medical centers but also in their homes and workplaces; thus offer cost saving and improve the quality of life. As an important result of these networks, patients gain more mobility and comfort around medical equipment. Further applications of WBANs with CS theory introduce abundant possibilities to improve the quality of collected medical data in order to make medical decisions for diagnostic and therapeutic purposes. Low-power and low sampling-rate proposed algorithms in this work for wireless healthcare systems based on CS theory show more opportunities for supporting mobility while monitoring the vital signal of cardiac conditions. The current medical systems can be further improved through our results by reducing costs, extending mobility, monitoring vital signal from several patients at the same time, and providing more adaptations for medical experts. In the end, better medical decisions with high accuracy for diagnostic and patient treatment purposes are gained.

We confirmed that the benefit of using wireless healthcare systems can be divided into two areas. One area is the use of new wireless technological solutions for individually based, multi parameter monitoring at home. It means patients with chronic diseases, as well as a growing number of seniors, will profit from treatment and medical monitoring at the home or workplace. Moreover, unlimited freedom of movement presupposes the use of wireless and even implanted biomedical sensors that greatly enhance home monitoring and follow-up of medical conditions. The second area of benefit occurs through increasing the efficiency of treatments. Today's biomedical sensors are mostly based on fixed/wired systems. Therefore, the cost of continuous monitoring and surveillance is already high and growing dramatically. That cost includes monitoring prior to treatment internally at the hospital, as well as post-monitoring. That is why the implementation of more flexible wireless healthcare systems leads to reduced hospitalization time and cost due to more rapid mobilization by stored and digitalized biomedical signals. The result would be enhanced decision-making for diagnostics, observation, and patient treatment. In this work, we have also confirmed that by applying CS theory the sparse signals, in terms of either the small number of non-zero coefficients or the small number of non-zero blocks, can be accurately represented as random linear combinations of a few measurements of such signals in data-independent random vectors. As an important conclusion, we are able to mention that the basic idea of CS theory is that when the biomedical signal is sparse in terms of the number of non-zero coefficients or the number of non-zero blocks, relatively few well-chosen observations suffice to reconstruct the original signal. Rather than measuring each sample and then computing a compressed representation, CS theory suggests that we can measure compressed representation directly. The results confirm that the CS as a new approach for the acquisition and recovery of sparse signal either on the number of non-zero coefficients or the number of non-zero blocks allows for a sampling-rate significantly below the classical Nyquist-rate. Figure 7.1 shows the conclusion of the results.

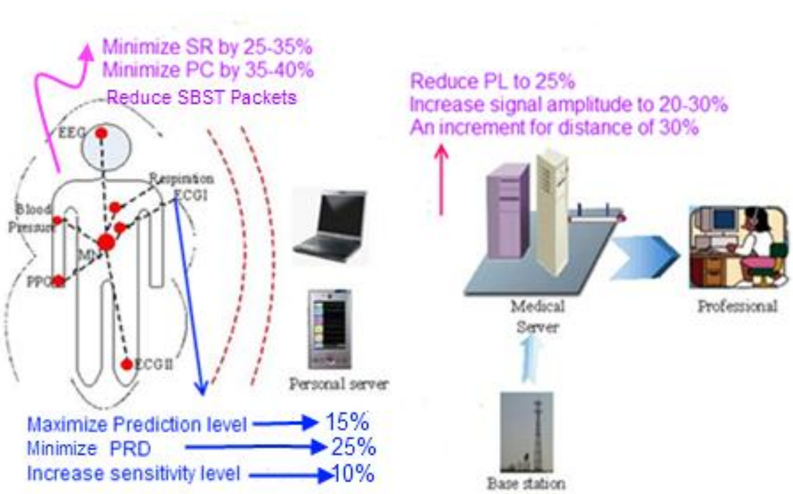


Fig. 7.1: Conclusion of the results

As depicted in the Fig.7.1, our results can be divided into three areas. One area is to employ the proposed algorithms to WBANs with single biomedical ECG signals. In this area, the simulation results illustrate an increment of 10% for sensitivity in receiving compressed ECG signals. The simulation results also illustrate a 25% reduction of PRD for EEG signals at the receiver side. In addition, they confirm the ability of CS to maximize the detection probability for received ECG signal at either GWs or APs. The second area of the result illustrates that proposed algorithms can be applied to WBANs with multiple biomedical signals and enhanced current health care systems to low-power wireless healthcare systems. In this area, the simulation results confirm that for a particular WBAN, including N biomedical signals, the sampling-rate can be reduced by 25-35% as well as power consumption by 35-40% without sacrificing the network's performance. In this area, simulation results also confirm that the number of SBST packets can be reduced by 9%. This ability can allow the probability of received SBST packets increase by 10%. The third area of the result illustrates that proposed channel model based on CS theory can be applied to WBANs in order to improve the features between BWSs and either GWs or APs. In this area, the results demonstrate that CS is able to maximize signal amplitude to 25-30% at the receiver as well as increase the distance between transmitter and receiver BWS to 30%. Moreover, they confirm that path loss can be reduced to 25%. The conclusions of each chapter are provided below:

Chapter 2 introduced WBANs and medical applications for wireless healthcare systems. This chapter emphasized that the WBANs concept has attracted the attention of medical and ICT researchers in recent years. They are already in use in medical areas, but their applications are limited. The main drawback of current systems is the location-specific nature of the system due to the use of fixed/wired systems. It confirmed that WBANs are expected to be a breakthrough technology in health care areas such as telemedicine and physical rehabilitation. As a result of this technology, patients gain more mobility and comfort of medical equipments. In addition to improve the quality of patient care, wireless medical telemetry systems are able to reduce the costs by decreasing the need to have medical personnel in close proximity to a patient at all times. Moreover, WBANs also serve the goal of reducing health care costs because they permit the remote monitoring of several patients simultaneously.

Chapter 3 demonstrated a review of CS theory and mathematical background for this theory. It confirmed that a combination of CS theory with WBANs is the optimal solution for achieving low power and low sampling rate networks. This chapter illustrated that the received signal at GWs or APs is a condensed representation of the sparse events. The CS provided the theoretical guarantee that the original signal can recover by the M random linear measurements. Moreover, it mentioned that CS is a revolutionary idea proposed recently to achieve the much lower sampling rate for sparse signal. This chapter emphasized that the signal representing sparsity in any orthogonal basis can be well reconstructed using ℓ_1 norm minimization, while satisfying the RIP condition for random measurement matrix Φ offered by compressed sensing theory and orthogonal base Ψ in any domain. In this chapter, we verified the validation for applying CS theory to WBANs and WSNs.

Chapter 4 presented our contributions to WBANs with single biomedical ECG signals. First contribution is based on the collaboration of CS theory and BSBL framework to compress any biomedical signal, including a sparse or non-sparse signal. Second contribution is obtained by combining CS theory and DTA approach for recovering the original biomedical signals at GW or APs for medical decisions. In this chapter, we validated the proposed algorithms for ECG signal as a sample for other biomedical signals. In this chapter, first the new reconstruction algorithm based on CS theory and the collaboration from BSBL is presented in order to recover sparse or non-sparse ECG signals. As expected, the proposed algorithm exhibits better performance on *SNR*, *CR*, and *PRD*. Second, the new algorithms with a contribution of CS approach, and SMS procedure based on DTA approach was investigated to establish a robust ultra-low-power model for normal and abnormal ECG signals. This algorithm was able to select the best fit for random sensing matrix of the CS approach. The simulation results confirmed that the Binary Toeplitz matrix provides the best SNR and compression performance with the highest energy efficiency for random sensing matrix. Third, we proposed a new detection algorithm for wireless ECG signal based on CS theory at gateways and access points with high probability and high accuracy at hospitals or medical centers for diagnostic and therapeutic purposes. The proposed algorithm consists of filtering, Shannon energy transformation, and peak clipping steps. The simulation results confirmed that the proposed algorithm achieves a significantly better detection rate in comparison with EMD-based method. We have also developed a new algorithm based on combining CS theory and wireless ECG framework. Our simulation results validate the suitability of the new algorithm for a real-time energy-efficient ECG compression on resource-constrained WBANs. As expected, our simulation results illustrate increments of 10% for sensitivity as well as 15% for the prediction level and a good level of quality for detection accuracy.

Chapter 5 presented our contributions to apply CS theory to WBANs with multiple biomedical signals. These contributions relied on a collaboration of CS theory, SMS procedure, LCDP algorithm, and testing approach. In this chapter, the simulation results on a particular WBAN with N wireless sensors demonstrated. Moreover, we 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 and power consumption. Second, we formulated the requirements to apply the CS theory to WBANs. From the simulation results, we investigated that sampling-rate can be reduced to 30% and power consumption to 40% without sacrificing performance. This chapter described how CS theory can be applied to WBANs in order to minimize cost, power, and delay. It discussed two key features, new sampling method, and new reconstruction method to recover the original biomedical data. This chapter also presented how CS theory can increase the lifetime of wireless nodes.

Chapter 6 illustrated new wireless channel model for WBANs based on CS theory. In this Chapter, we first described how to employ the CS theory in MFCs for achieving a universal model for MFCs. Second, we formulated the requirements to apply the CS theory to MFCs. Our simulation results show PL can be reduced by 25% and BER by 10% by employing CS to MFCs. The simulation results also indicate that a good level of quality of MFCs can be achieved when signal amplitude at GW increases by 25% and distance between transmitter and receiver wireless sensor increases by 30%.

Table 7.1 summarizes the various solutions provided by the proposed algorithms in this dissertation. Table 7.2 shows a summary of the results for each proposed algorithm.

Table7.1: Summary of the proposed solutions

Requirement for WBANs/WSNs	**Solution provided by the proposed work**	**Chapter Reference**
Low sampling-rate approach	CS theory	Chapter 3
Reconstruction of compressed biomedical data	Integration of CS with BSBL framework	Chapter 4
Low path loss MFCs	Channel model based on CS theory	Chapter 6
Best fit for random sensing matrix Φ	SMS algorithm	Chapter 4
High Detection rate for received biomedical signals at GWs/APs	LCDP algorithm	Chapter 4
Low data-rate algorithm for networks with multiple signals	CS theory	Chapters 5

Highly reliable algorithm for networks with multiple signals	Contribution from CS and SBST approach	Chapter 5

Table 7.2: Summary of the results for each proposed algorithm

Proposed Algorithm	Results
Advanced BSBL	► **PRD ↓ 25%**
SMS	► **SR ↓ 25%** ► **PC ↓ 30%**
LCDP	► **Sensitivity ↑ 10%**
SBST	► **Number of SBST Packets ↓ 9%** ► **Probability of Receives SBST Packets ↑ 10%**
New Channel Model Based on CS Theory	► **PL ↓ 25%** ► **Distance between transmitter and receiver nodes ↑ 30%** ► **Signal Amplitude ↑ 10%**

7.2. Future Work

The future work for this thesis can be divided into the following areas:

1) We have simulated the benefit of CS theory to wireless ECG systems for five records of ECG signals. Our future work will involve developing the CS theory to other records of ECG signals, including abnormal records.

2) We have simulated the benefit of CS upon normal and abnormal ECG signals to provide a robust sampling approach. Our future work involves developing the CS theory to other types of biomedical signals such as EMG and EEG signals.

3) We have simulated the benefit of CS theory to WBANs for the on-body to on-body scenario. Our future work will involve developing the CS theory to other scenarios such as on-body to in-body, and in-body to on-body. We have also examined MFCs with CS for a particular ECG signal. It will be another part of our future work to employ MFCs with CS theory for other types of biomedical signals.

4) Our future work also involves fabricating biomedical wireless sensors based on the results of this work.

List of Publications

Journals

Published Journal Papers

[1] M.Balouchestani, K.Raahemifar, S.Krishnan ,“ Robust Wireless Sensor Networks with Compressed sensing theory,” *Communications in Computer and Information Science Journal of Springer*, vol.293, pp.608-619,2012.

[2] M.Balouchestani, K.Raahemifar, S.Krishnan, “Low Sampling-rate Algorithm for ECG Signals with Compressed Sensing Theory,” *Signal Image and Video Processing Journal of Springer*, vol. 72, pp.1-8, March 2013.

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Accepted Journal Papers

[1] M.Balouchestani, K.Raahemifar, S.Krishnan,” Implementation of Reconstruction and Detection Algorithms for ECG Signal Compression on Wireless Body Sensor Networks,” Accepted in *IEEE Transaction on Instrumentation and Measurements*, May 2013.

[2] M.Balouchestani, K.Raahemifar, S.Krishnan,” Techniques for Accurate Normal and Abnormal ECG Signal Processing with Compressed Sensing Theory,” Accepted in *Elsevier Science and Technology Journal*, May 2013.

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[4] M.Balouchestani, K.Raahemifar, S.Krishnan," Robust Ultra-Low-Power Algorithm for Normal and Abnormal ECG Signals Based on Compressed Sensing Theory." Accepted in *Elsevier Science and Technology Journal*, May 2013.

Submitted Journal Paper

[1] M.Balouchestani, K.Raahemifar, S.Krishnan, " Robust Algorithms for Wireless ECG Systems Based on Compressed Sensing Theory," Submitted to *IEEE Journal of Biomedical and Health Information",* June 2013.

Conference Papers

Published Conference Papers

[1] M.Balouchestani, K.Raahemifar,S.Krishnan,"Wireless Body Area Networks with Compressed Sensing Theory," *IEEE-ICME International Conference on Complex Medical Engineering* ,Kobe, Japan , pp.364,369, July 2012.

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[5] 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.

[6] M.Balouchestani, K.Raahemifar, S.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*

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