Performance Evaluation of Compressive Sensing Technique for ECG Signal in WBAN

Karthik .N .B[1], Rajashekar .K[2]

[1]PG Scholar, Digital Electronics, GM Institute of Technology, India

[2] Assistant professor, Electronics and communication engineering, GM Institute of Technology, India

Abstract: ***Wireless Body Area Network (WBAN) is a class of Wireless Sensor Network (WSN). WBAN consist Biomedical Wireless Sensors (BWs), these BWs sense the vital signals from human body and transmit through Gateway (GW) to access point (APs) at hospital for therapeutic and diagnostic purposes. Electrocardiogram (ECG) signals are commonly used for healthcare centers of WBAN; it generates bioelectric current waveforms of heart rhythm and specifies underlying heart diseases. WBAN suffer some problems are limited storage capacity, processing, power, time, transmission and sampling rate. Compressed sensing (CS) with Block Sparse Bayesian Learning (BSBL) techniques used to improvements of these parameters. Furthermore, performance evaluation of ECG monitoring shows that cost saving and improving the quality. The simulation result performs the good quality of Signal-to-Noise Ratio (SNR) increases while Percentage in Root-mean-square Difference (PRD) decreases.***

Keywords: ECG Signal, Compressed Sensing, Dynamic Thresholding Approach, Block Sparse Bayesian learning

1. Introduction

Now a day's wireless communication technology is increases rapidly in healthcare systems. WBAN consists of BWs implanted on the human bodies to provide ECG monitoring to medical centers with constraints of anytime and any location of patient handled by personal device e.g. Personal Digital Assistant (PDA) or Smart phone. ECG waveforms are used to represent the information from the heart for the diagnostic purposes of heart diseases. Long ECG records increases the quantity of data so compression is required for transmission, power consumption, storage and time. The bandwidth of signal always greater than 2Ω samples in nyquist-rate these results more sampling-rate. To overcome this problem CS theory is used [1]. The CS shows that the bio-sparse signals of WBAN can be exactly reconstructed original signal using ℓ1 norm minimization by important two conditions. First, number of random matrix measurements must satisfy Restricted Isomerty Property (RIP) condition and represents the sparsity of signal in any orthogonal basis Ψ [2].

The remaining section of this paper organized as follows, Section II describes the overview of compressed sensing. Section III describes the proposed approach. Section IV shows the results simulation. Scope of project deals with section V. The paper concludes with Section VI represents future works.

2. Overview of compressed sensing

The conventional sampling method says that minimum 2Ω samples require to recover original signal, these increases the SR and transmission-rate to reduce data significantly Compressed sensing(CS) is used. CS method is a new sampling technique, it recovers original signal below the 2Ωsamples nyquist-rate by random measurements in small number of quantity from compressed signal. Any compressible signal has few/more samples or large/small samples represent as sparse signal D in $\mathbb{R}^N$[3] can be expressed like:

$$D = \sum_{i=1}^{N} Ci\ \Psi i \qquad (1)$$

Therefore, the compressed signal written as:

$$[\mathbf{C}]_{M\times 1} = [\mathbf{\Phi}]_{M\times N}\,[\mathbf{D}]_{N\times 1} \qquad (2)$$

Thus, the compressed signal also re-written as:

$$[\mathbf{C}]_{M\times 1} = [\mathbf{\Phi}]_{M\times N}[\mathbf{\Psi}]_{N\times N}[\mathbf{C}]_{N\times 1} = [\mathbf{\Theta}]_{M\times N}[\mathbf{C}]_{N\times 1} \qquad (3)$$

Where [Φ] represents incoherent property with the signal sparsity in orthogonal basis[Ψ] for small number of random linear measurements matrix Φ and [Θ] satisfies RIP condition for detection probability at receiver side. The original signal is reconstructed by$\ell 1$-norm minimization from compressed signal. The high level of accuracy and detection probability is achieved via $\ell 1$-norm minimization and solving convex optimization problem ($\|Dn\|\ \sum_n |Dn|$) represented as:

$$\min \|D\|_1 \text{ subject to } C=\Phi D \qquad (4)$$

$$D\in\mathbb{R}^N$$

To satisfy the accuracy of the recovery there are three conditions. First, Φ and Θ satisfy RIP condition. Second coefficients (N), non-zero coefficients (K) and number of random linear measurements (M)must satisfy the equation (5):

$$M \leq K/C\,(\log N) \qquad (5)$$

Third, the original signal D matrix Φ for any vectorαmust satisfy the following condition ε >0:

$$1\text{-}\varepsilon \leq \|\Phi\alpha\|_2/\|\alpha\|2 \leq 1+\varepsilon \qquad (6)$$

Consider M ≥ K for M ×K linear equation system, where K is unknown. To find out k-sparsity of original signal and contains the number of random linear measurements matrix Φ and needed to reconstruction of bio-sparse signal without knowing the priori about the original biomedical signal.

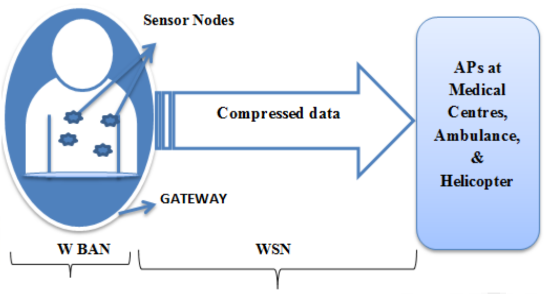

Figure 1: CS in WBANs

Figure1 shows the WBAN structure for CS theory; the biomedical signals are compress at BWs. The collected compressed data are transmitted wirelessly via Gateway to Access Points (APs) at medical centres, ambulance and helicopter [4] to recover of the original signal from compressed data for diagnostic and therapeutic purposes.
The received signal can be expressed as:

$$[\mathbf{C}]_{M\times 1} = [\mathbf{\Phi}]_{M\times N}\,[\mathbf{D}]_{N\times 1} \tag{7}$$

Consequently, the sparsity of received signal can be expressed as:

$$\begin{pmatrix} C_1 \\ \vdots \\ C_M \end{pmatrix} = \begin{pmatrix} \Phi_{11} & \cdots & \Phi_{1N} \\ \vdots & \vdots & \vdots \\ \Phi_{M1} & \cdots & \Phi_{MN} \end{pmatrix} \begin{pmatrix} D_1 \\ \vdots \\ D_N \end{pmatrix} \tag{8}$$

Finally, simulation results show the higher transmission rateanddetection probability of data transmission by employing the CS the WBANs.

3. Proposed Method

CS approach with BSBL framework and DTA procedure is use to compress ECG signal for normal and abnormal signal for sparse and non-sparse signal to achieve better performance. The signal is portioned into a concatenation on non-overlapping blocks and a few of blocks are non-zero with block structure [5]. Applying pruning mechanism the blocks are pruned out [6] BSBL framework is still effective while signal has no structure. The covariance matrix of the signal is obtained by block partition. Further generates length of each block for real-time transmission and length should be short [7].To recover original signal with fewer samples incorporate heartbeats in one block. The Compression Ratio (CR), the Structural Similarity Index (SSI), and Percentage PRD are calculated as performance measures in proposed approach.
The CR can be expressed as [8]:

$$CR = N\,/M \times 100 \tag{9}$$

M and *N* are the number of random linear measurements and number of samples in ECG signals respectively. Further, simulation results indicate that satisfying quality of Sampling rate (SR) can be achieved.
The SSI is defined as [9]:

$$SSI = (C\,/\,D) \times 100 \tag{10}$$

C and *D*are the recovered and original ECG signals respectively. It measures the similarity between the recovered and original ECG signals and Higher *SSI* means better recovery quality.
The PRD is measured as [10]:

$$PRD = (\|D - C\|_2 / \|D\|_2) \times 100) \tag{11}$$

PRD is a relationship between the measured PRD and diagnostic distortion is recognized for ECG signals and classifies the different values of PRD based on the signal quality of reconstruction approach.

4. Simulation Results

In this section, the reconstruction algorithm based on BSBL framework is applied to improve SNR, CR, SR, and quality of the recovered ECG signals. The quality for SNR can be achieved by minimizing CR. The simulation results based on the MIT-BIH ECG databases [11] in non-CS and CS scenarios. For the simulations normal (record 202) ECG signal and abnormal (record 203) ECG signal are taken into consideration.

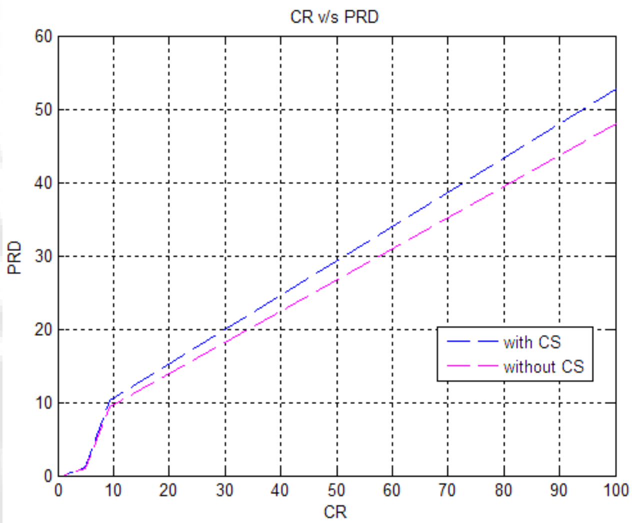

Figure 2 (a): ECG record 202 with CS and non-CS scenarios.

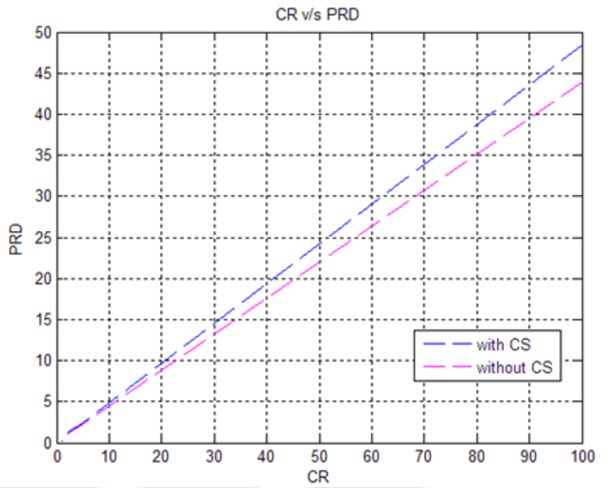

Figure 2 (b): ECG record 203 with CS and non-CS scenarios

Figure2 (a) and (b) Shows the simulation result for record of 202 and 203 in CS and non-CS theory scenarios from the MIT database and compares the output CS method with respect to random binary sensing matrix to non-CS method. The output PRD is measured by comparing PRD and random binary sensing matrix for Normal and abnormal signals from MIT-BIH ECG database.

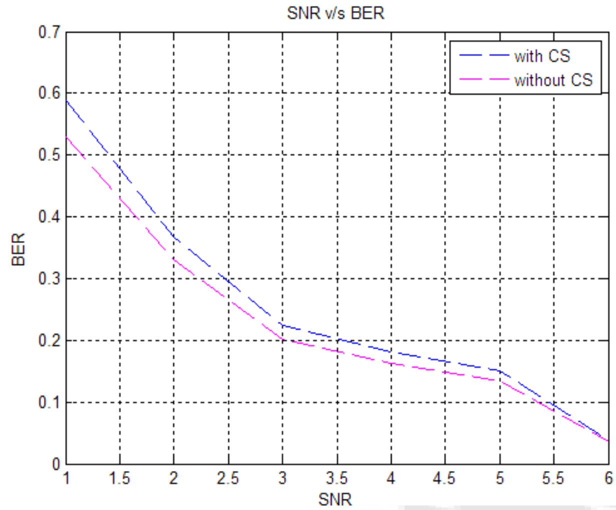

Figure 3 (a): ECG record 202 Comparison for BER

Figure3 (a) and (b) shows the Bit Error Rate (BER) of recovered ECG signal for normal ECG record (202) and abnormal ECG record (203). The packet loss probability defines BER and exposes excellent robustness for ECG signals. The effective BER can be reduced by using adaptive sampling and higher packet transmission increases [12].Higher packet transmission probability reduces the packet delay and power budget of an ECG signal and power budget can be optimizing by increasing packet transmission probability.

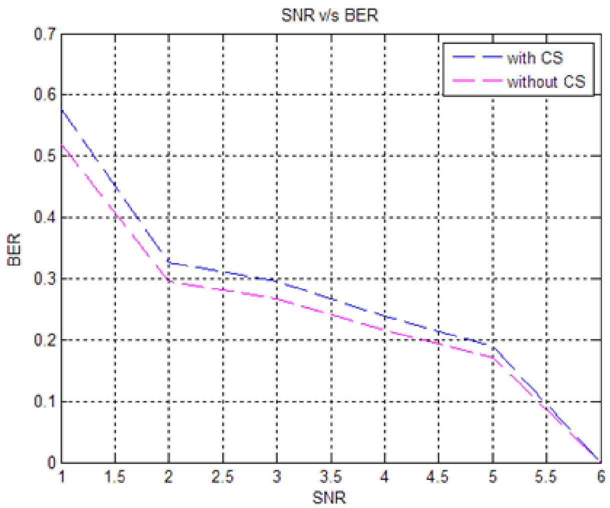

Figure 3 (b): ECG record 203Comparison for BER

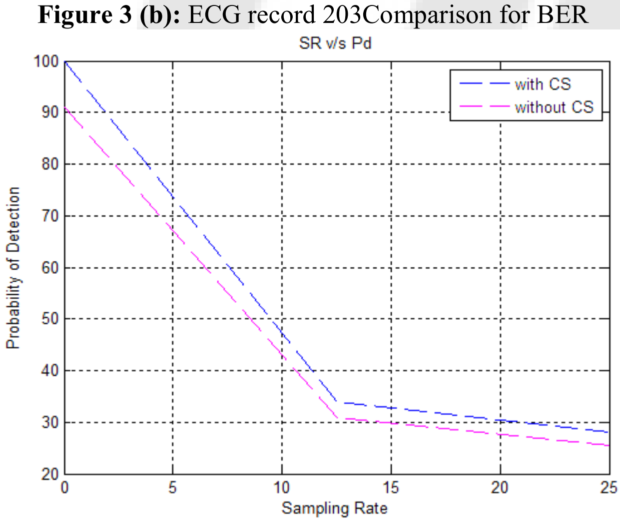

Figure 4 (a): ECG record 202POD ECG signals versus SR

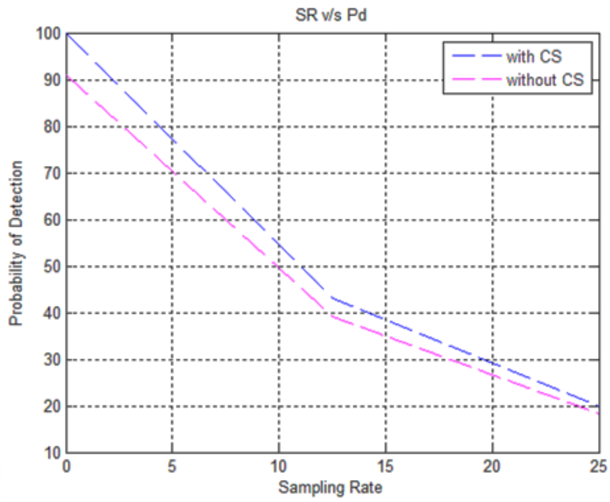

Figure 4 (b): ECG record 203POD ECG signals versus SR

Figure4 (a) and (b) shows the Probability of detection (POD) ECG signals versus SR this illustrates the sampling-rate for random binary matrix with CS theory. SR is reduced by the nyquist rate without sacrificing the performance.

5. Scope of the project

The scope of the project is to improving the sampling rate, while PRD will decreases with increasing good quality of signal to noise these results good transmission rate for communication links applying new technique of BSBL framework

6. Conclusion

This paper presents the implementation of CS with BSBL framework and DTA to establish a robust and low sampling-rate algorithm for normal and abnormal ECG signals. As expected, the performance evaluation exhibits better performance on SNR, CR, and PRD. Simulation results indicate that good level of quality of CR can be achieved when PRD decreases by applying the CS theory. The future work involves establish the CS theory, BSBL, and DTA procedure for other records of ECG signals.

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Author Profile

Karthik N B is PG scholar in Digital Electronics Department, GMIT College, Davangere, India. Completed BE in Electronics and Communication Engineering in Karavali Institute of Technology in Mangalore in 2011 and completed Diploma in Electronics and communication engineering in DRR polytechnic in 2005. Intersted fields Wireless Sensor Network, bio-medical signal processing

Rajashekar Kunabeva is affiliated with GMIT, Davangere where he is serving as assistant Professor and currently pursuing Ph.D under VTU, India. He has 10 years of teaching experience, above 4 years of industry experience in Network Administration and is a certified MCP. He is recipient of the "Best paper" award at National conference held at AIT, Bangalore, India in December 2010.His research interests are WSN, WBAN, Biomedical Signal Processing, Mobile and Soft computing Techniques. He is a life member of ISTE.