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Energy Efficient Sampling approach of Compressed Sensing for Wireless Body Area Network

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***Abstract*-Compressed sensing is a recent perspective for acquisition and reconstruction of sparse signals that allow sampling rate notably below the classical Nyquist rate. This paper proposes a compressed sensing based approach for ECG signal compression with aim of low energy consumption and low sampling rate in wireless body area network (WBAN). The WBANs collect and transfer the biomedical data by using various biomedical wireless sensors attached in or on the human body for health monitoring, biofeedback and ambient assisted living. New and low sampling theory based on compressed sensing (CS) theory to WBANs with ECG biomedical signal. The ECG signal is selected as a sample signal for our analysis. The reason for selecting ECG signal as a sample is that ECG signals usually have a repetitive pattern they can be compressed and there is a need to explore compressed sensing for ECG signals. The Simulation results show that compressed sensing for ECG compression.**

Keywords- ECG signal; Compressed Sensing; Wireless Body Area Network.

I. INTRODUCTION

ECG signals are a non-invasive technique used in health care systems**.** A long-term record of ECG signal is regarding the heart for diagnostic and therapeutic purposes. So that data quantity grows significantly, and compression is needed for reducing the storage, transmission times, and power consumption [1]. The ECG signals usually show the redundancy between adjacent heartbeats due to their semi-periodic structure. This redundancy provides a high degree of common support between consecutive heartbeats making them a good candidate for compression. CS theory to wireless ECG provides low data rate, require low transmitting power, and longer battery life for diagnostic and therapeutic purposes. The wireless ECG systems offer two major advantages over the current health monitoring systems: 1) it does not limit user's mobility; 2) It allows monitoring of ECG signals outside hospitals and medical centers for early diagnosis [2]. The compressed sensing with the biomedical ECG signal is selected as sample signal for our analysis.

The Recent Emerging technique of CS in which the signal is sampled and concurrently compressed. The biomedical signal is sparse in terms of either a number of non-zero coefficients or a number of non-zero blocks. The compressed sensing theory is to reconstruct the original signal from few chosen observations and directly measure compressed representation. The CS is presented 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. 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 [3]. Reduced number of acquired samples is beneficial for WBAN. It mitigates the requirements imposed on sensor storage and processing capabilities.

Compressed sensing has advantages of 1. It provides simpler hardware implementations for the encoder. 2. Low computational complexity 3. Small traffic volume and small time delay. 3. It able to reconstruct the sparse signal from a small number of linear projections. Compressed sensing is based on exploiting sparsity. Sparse signals are those that can be represented as a combination of a small number of projections on a particular basis. (This new basis must be incoherent with the original basis.) Because of sparsity, the same signal can be represented with a smaller amount of data while still allowing for accurate reconstruction [4]. In non-compressed sensing methods, one would first acquire a large amount of data, compute an appropriate basis and projections on it, and then transmit these projections and the basis used. This is wasteful of resources since many more data points are initially collected than are transmitted. In compressed sensing, a basis is chosen that will approximately represent any input sparse signal, as long as there is some allowable margin of error for reconstruction.

II. COMPRESSED SENSING

The CS theory replaces the conventional sampling and reconstruction operation with a general random linear measurement process and an optimization scheme in order to recover original signal from a small number of random measurements.

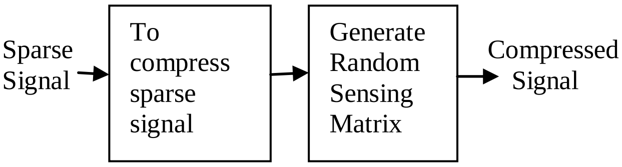


Fig. 1. CS transmitter

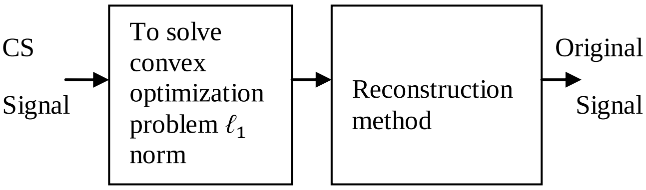


Fig. 2. CS receiver

A. *Basic Theorem*

The sampling approaches depend on the Shannon sampling theorem. This theory says a signal can be represented in its samples and recovered when the sampling frequency is greater than or equal to the twice the highest frequency. This sampling theorem requires a large number of samples. The sampling theorem approaches have two disadvantages. First, they create huge unendurable samples and produces large bandwidth. Second, produce a large amount of redundant digital samples for some biomedical signals. So that it is desirable to reduce the number of acquired biomedical samples by utilizing sparsity [5] [6]. The main motivation of new sampling approach of compressed sensing is to recover the signal from fewer numbers of samples with reconstruction operation with a general random linear measurement process and an optimization scheme. CS is a new approach for the acquisition and reconstruction of sparse signals either from the number of non-zero entries. This theory states a small number of random linear measurements of compressible signals contain enough information to recover and process the original signal [7]. The CS theory states sparse or compressible signals such as some biomedical signals can be well recovered when minimizing $\ell 1$ norm optimization while satisfying the RIP condition for the random measurement matrix Φ and orthogonal basis ψ [8]. 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≪Nand can be well recovered using M projections or measurements such that K ≤ 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. Any compressible or sparse signal X in $\mathbb{R}^{N}$can be expressed as;

$$X=\sum_{i=1}^{N} D_i \Psi_i \tag{1}$$

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

$$[\mathbb{S}]_{M\times 1}=[\Phi]_{M\times N}[X]_{N\times 1} \tag{2}$$

Thus, the compressed signal is found as:

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

[Φ] And [Θ] have two interesting and useful properties. First, they are incoherent with the basis [Ψ]. 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 [9]. 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 X∈$\mathbb{R}^N$ down to $\mathbb{S}$∈$\mathbb{R}^M$. In the second step, the CS theory offers a reconstruction algorithm under certain conditions with enough accuracy to recover, original signal *D* from the compressed signal. In CS, the random measurement matrix [Φ] is a key component for compressing the input signals. 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 [Ψ] and random measurement matrix [Φ]. 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 matrixΦ, which is offered by compressed sensing theory and orthogonal base Ψ in any domain [12] [13]. Therefore, we can exactly reconstruct, with a very high level of accuracy, the original signal X with high probability via ℓ_1 by solving the following convex optimization problem

$$(\| X \|_1 = \sum_N |X|)$$

$$\min \| X \|_1 \text{ Subject } \mathbb{S} = \Phi X \tag{4}$$

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

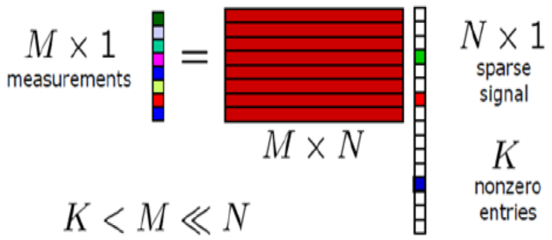
However, certain conditions must be met to guarantee the accuracy of the recovery. First, the number of random linear measurements, coefficients, and non-zero coefficients must satisfy the following equation

$$M \leq K/C(\log N) \tag{5}$$

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. The second is to guarantee robust and efficient recovery of the k-sparse signal; the sensing matrix $\mathbf{\Phi}$ must obey the key Restricted Isometry Property (RIP)

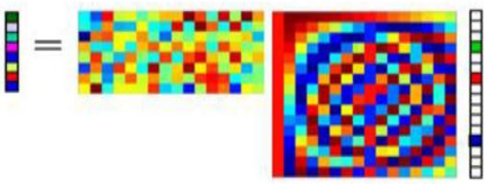
$$(1-\delta_\kappa) \parallel X \parallel_2^2 \leq \parallel \Phi X \parallel_2^2 \leq (1+\delta_\kappa) \parallel X \parallel_2^2 \qquad (6)$$

for all k-sparse vectors X and some constant $0 < \delta_\kappa < 1$. In order to recover *K-sparsity* of the original signal, now we have M×Ksystem of linear equations, with M equations and K unknowns, and since M $\geq K$, it is possible to find the *K-sparsity* of the original signal.



$[\mathbb{S}]_{M\times1}$ = $[\Phi]_{M\times N}$ $[X]_{N\times1}$

Fig.3. A pictorial scheme of compressed signal.



$[\mathbb{S}]_{M\times1}$= $[\Phi]_{M\times N}$ $[\Psi]_{N\times N}$ $[D]_{N\times1}$

Fig. 4. A pictorial structure to generate compressed signal.

Therefore, in the CS scenario, we can focus only on random linear measurements instead of N samples such that M≪N. The CS theory also offers a reconstruction algorithm to recover original signal X from the compressed signal $\mathbb{S}$ only with M random linear measurements [10].

B. *Application of CS in WBAN*

WBAN as a subset of WSNs consists of wireless sensor nodes attached to or on the human body for health monitoring, intelligent emergency care management systems, intensive care, surgery and diagnosis purposes and ubiquitous wireless healthcare applications by moving wireless communication technologies to BANs or Personal area network for carrying the biomedical data. In the WBANs the biomedical wireless sensors collect and transmit the patient's data to medical centers via a gateway. This improves the quality of patient care and efficiency. WBANs reduce the cost of health care because they permit the remote monitoring of several patients simultaneously. The CS theory, as an emerging data compression technique, allows some important constraints in WBANs. Medical applications of WBANs based on CS theory involves continuous waveform sampling of biomedical signals, monitoring of vital signal information, and low rate power remote control of medical devices.

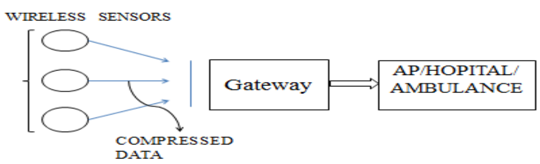


Fig. 5 . CS theory in WBAN

As shown, the biomedical signals are compressed by wireless sensors. The compressed biomedical data are collected and then transmitted to access point (APs). The APs are recovered compressed biomedical data for diagnostic and therapeutic purposes. The received vector in GW can be written as:

$$[\mathbb{S}]_{M\times1}=[\Phi]_{M\times N}[X]_{N\times1}$$

The CS in WBANs can provide a higher transmission, a lower time delay and higher probability of success of data transmission [11]. CS theory in WBANs with the low sampling rate and power consumption.

C. *Performance Measure*

The performance metrics of the compression method is compression ratio (CR), percentage Root mean square difference (PRD) and Structural Similarity Index (SSI), and PRD is employed in our approach [14]. The CR is a measure of how much data to be reduced when reconstructing the signal X.

$$\text{CR} = N/M \times 100 \qquad (7)$$

where M and N are the number of random linear measurements and the number of samples in ECG signals, respectively. The SSI metric is defined as:

$$\mathrm{SSI} = (\mathbb{S}/\mathrm{X}) \times 100 \quad (8)$$

Where X and $\mathbb{S}$ are original and recovered ECG signals, respectively. This metric measures the similarity between the recovered and original ECG signals. Higher SSI means better recovery quality The PRD is computed as:

$$\mathrm{PRD} = (\| X - \mathbb{S} \|_2 / \| \mathrm{X} \|_2) \times 100 \quad (9)$$

The value of PRD shows the quality of reconstruction approaches. Percentage root mean square difference is percentage measure of the difference between original and recovered signal.

III. SIMULATION RESULTS

The simulation results show the compressed sensing of ECG signal and reconstructed signal of ECG signal. Experiments are carried out over a 10-seconds long leads ECG signal extracted from MIT-BIH ECG compression test database. To validate the simulation results ECG signals from records13005_02, 13139_03, 13030_02 from MIT-BIH. The record 13005_02 is included in the set to evaluate the performance of the algorithm. MIT-BIH ECG compression test database contains 168 short ECG recordings (20.48 seconds each) and the sampling frequency is 250 Hz and resolution of 12bits. The proposed method achieves a good compression ratio for low PRDs that correspond to high quality in the reconstruction. The waveforms of the record 131005_02 given by the proposed the compression scheme is visually evaluated in Fig. 6. The reconstructed signal remains close to the original signal.

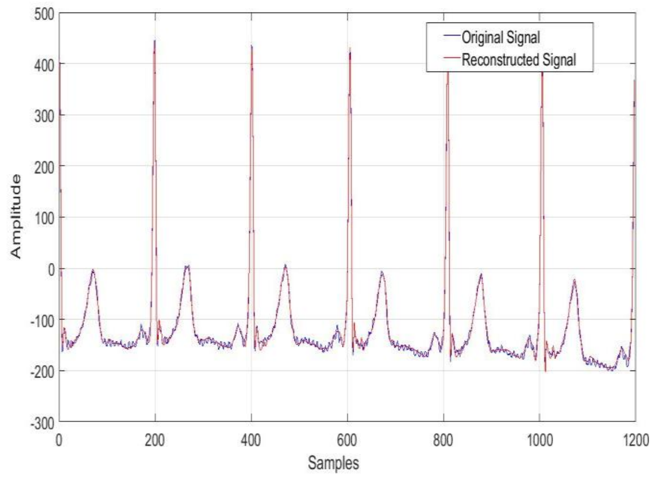


Fig. 6 Recovered Signals

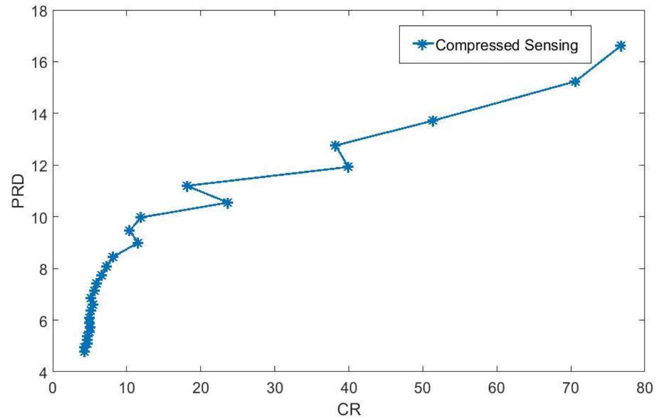


Fig. 7. ECG record13005_02 with compressed sensing.

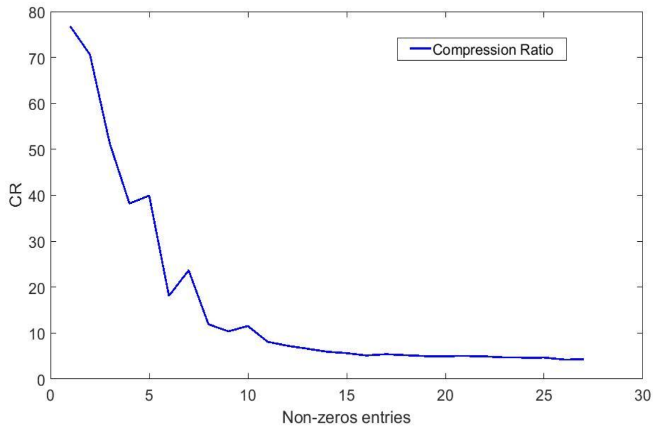


Fig. 8. CR in terms of non-zero entries

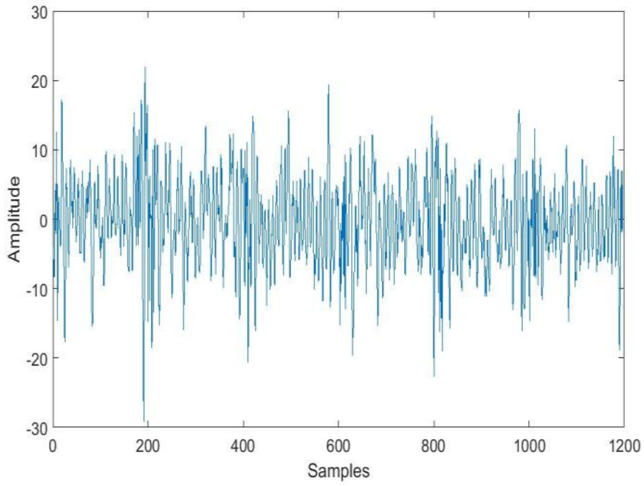


Fig. 9. Error Signal

IV. CONCLUSION

This paper presents a new approach of CS for WBAN. Compressed sensing method is an acquisition and recovery of sparse signals that allow sampling rate less than classical Nyquist rate. Compressed sensing is combining of sampling and reconstruction method. Simulation results show that good level quality of CR can be achieved by applying CS theory of ECG signals from MIT-BIH compression test database. The new energy efficient sampling of CS theory applied to WBAN with benefit of low sampling rate and low power consumption in order to give diagnostic purposes and biofeedback and ambient assisted living. The future work establishes the CS theory to other signals like EEG, EMG, brain activity, heart rate in WBAN.

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