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A High Reliability Detection Algorithm for Wireless ECG Systems Based on Compressed Sensing Theory

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Abstract— Wireless Body Area Networks (WBANs) consist of small intelligent biomedical wireless sensors attached on or implanted in the body to collect vital biomedical data from the human body providing Continuous Health Monitoring Systems (CHMS). The WBANs promise to be a key element in wireless electrocardiogram (ECG) systems for next-generation. ECG signals are widely used in health care systems as a noninvasive technique for diagnosis of heart conditions. However, the use of conventional ECG system is restricted by patient's mobility, transmission capacity, and physical size. Aforementioned highlights the need and advantage of wireless ECG systems with low sampling-rate and low power consumption. With this in mind, Compressed Sensing (CS) procedure as a new sampling approach and the collaboration from Shannon Energy Transformation (SET) and Peak Finding Schemes (PFS) is used to provide a robust low-complexity detection algorithm in gateways and access points in the hospitals and medical centers with high probability and enough accuracy. Advanced wireless ECG systems based on our approach will be able to deliver healthcare not only to patients in hospitals and medical centers; but also at their homes and workplaces thus offering cost saving, and improving the quality of life. Our simulation results show an increment of 0.1% for sensitivity as well as 1.5% for the prediction level and detection accuracy.

Index Terms-* *Wireless ECG systems, Detection accuracy, Compressed sensing theory, Prediction level.

I. INTRODUCTION

Wireless ECG systems are expected to be a breakthrough in Information Communication Technology (ICT) and in healthcare areas such as hospital and home care, mobile health, electronic health. Wireless ECG systems play an important role in remote cardiac patient monitoring, intelligent emergency care management systems, and ubiquitous wireless healthcare applications. The biomedical wireless sensors collect and transmit the vital signals of cardiac patients wirelessly. The current ECG systems are restricted by size, patient's mobility, power, and transmission capacity. Therefore, the current ECG systems need to be further developed in order to accommodate user's mobility and allow wireless monitoring of several patients at the same time. The ECG signals generally illustrate redundancy between adjacent heartbeats due to its semi-periodic structure. It is evident that this redundancy provides a high fraction of common support between consecutive heartbeats that is a good candidate for compression. The compressed sensing is a revolutionary idea for the acquisition and recovery of sparse signals that enables sampling-rate significantly below the classical Nyquist-rate. The CS theory says a small number of random linear measurements of sparse signals contain enough information to collect, process, transmit, and recover the original signal [1].The signal representing sparsity in any orthogonal basis can be well reconstructed using ℓ_1 norm minimization, while satisfying the Restricted Isomerty Property (RIP) condition for random measurement matrix Φ which offers by compressed sensing theory and orthogonal Ψ in any domain [2]. In this paper a new detection algorithm is proposed for wireless ECG systems based on CS theory. The proposed technique takes into account gateways and access points typically present at hospital or medical centers. Moreover, this paper presents a contribution of CS approach with wireless ECG framework to establish a high reliability detection algorithm for wireless ECG systems. Our simulation results illustrate an increment of 0.1% for sensitivity as well as 1.5% for the prediction level and a good level of quality for detection wireless ECG systems with high probability and enough accuracy. The structure of this paper is organized as follows: Section II provides an overview of CS theory in general and specifically for wireless ECG systems. In Section III, we propose our algorithms. Simulation results are presented in Section IV. The conclusion is drawn in Section V.

II. OVERVIEW OF COMPRESSED SENSING

Any compressible signal in $\mathbb{R}^N$ can be expressed as [3]:

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

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

$$[\mathbb{C}]_{M\times 1} = [\Phi]_{M\times N}[D]_{N\times 1} . \tag{2}$$

Thus, the compressed signal is found as:

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

Fortunately, $[\Phi]$ and $[\Theta]$ have two interesting and useful properties. First, they are incoherent with the basis $[\Psi]$. Second, they have the RIP with high probability, which is suitable condition for recovering the original signal in the receiver side [1]. Thus, CS scenario has two important steps. First step in CS offers a stable measurement matrix $\Phi_{M\times N}$ to ensure that the main information in any compressible signal is not distorted by the dimensionality reduction from $D \in \mathbb{R}^N$ down to $\mathbb{C} \in \mathbb{R}^M$. In the second step, the CS theory offers a reconstruction algorithm under certain condition and enough accuracy to recover original signal D from the compressed signal. Therefore, we can exactly reconstruct the original signal D with high probability via ℓ_1 norm by solving the following convex optimization problem ($\| D \|_1 = \sum_n |D_n|$):

$$\min_{D \in \mathbb{R}^N} \| D \|_1 \quad \text{subject to} \quad \mathbb{C} = \Phi \Psi D. \tag{4}$$

Certain conditions need to be met to guarantee the accuracy of this recovery. Firstly, the number of random linear measurements, coefficients, and non-zero coefficients must satisfy the following equation [4]:

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

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

$$1 - \varepsilon \le \| \Phi a \|_2 / \| a \|_2 \le 1 + \varepsilon, \tag{6}$$

where satisfies RIP property 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. It is possible to find out the *K-sparsity* of the original signal, because of $M \ge K$. Figure 1 show a wireless ECG system based on CS theory. As it can be seen the ECG signals are compressed by biomedical wireless sensors. The collected compressed ECG biomedical data are then transmitted wirelessly to Access Points (APs) at hospital, ambulance, or helicopter [5] via gateways. The APs recover compressed biomedical data for diagnostic and therapeutic purposes.

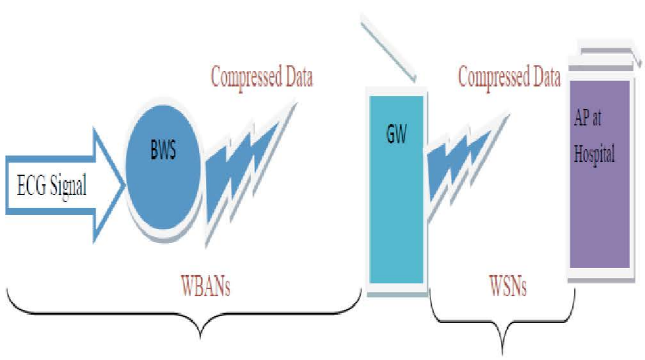

Fig.1: Wireless ECG systems based on CS theory

III. PROPOSED DETECTION ALGORITHM

The wireless ECG systems provide vital information of the heart to physicians and medical staff at anytime and anywhere by removing constraints of time and location of patients while increasing both the mobility and the quality of healthcare systems. The reliability of the wireless ECG systems is particularly important to ensure that gateways and APs receive ECG signal with high accuracy for diagnostic and therapeutic purposes. In this Section, the low complexity and high reliability detection algorithm for wireless ECG system is presented. Generally, the ECG signal includes of P-wave, QRS complex, T and U-wave. The abnormal ECG signal has narrow and wide-QRS complexes [6]. 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 stage after the compression, including digital filtering and linear transformation to generate ECG features such as QRS complex, and 2. Decision make stage is performed on compressed ECG signal to locate R-peak. The digital filtering is performed to limit the filtering operation to just once. The decision stage is based on Adaptive Threshold Mechanism (ATM) to detect the ECG signal. The threshold value depends on RP-intervals and R-peaks and is updated periodically based on ECG features [7]. The Hamming Window (HM) for the feature extraction stage and the PFS algorithm for the decision stage are applied to simulate the high reliability detection algorithm [8]. The output signal of the filtering process with HM is a bipolar signal, and thus a rectification process is employed to prevent the detection problems where ECG signals change polarity due to bipolar R-part and negative QRS-part. By employing the SET algorithm in the feature extraction stage, the energy values E_s smaller than the threshold is set to zero and other energy values are retained. Table 1 illustrates the proposed algorithm.

Table 1: The detection algorithm for wireless ECG systems

1) Received ECG signal at GW		
2)Feature Extraction Stage	- Digital Filtering - Energy Transformation	
Target: Determine the approximate location of the ECG parts	Tools in C^{++}	1) Hamming tool in C++ to accentuate the ECG parts 2) SET Tool to eliminate the unwanted signals
3) Decision Stage **Target**: Recognize the accurate location of the ECG parts, including QRS complex part	- Peak Finding Schemes - Peak Clipping	
	Tools in C^{++}	1) Peak finding 2) Peak clipping
1) Detect ECG features for medical purposes		

The adaptive-threshold is defined as [9]:

$$A_T = 0.25(1/M\sum_{n=1}^{M}(E_s[n]-E)^2)^{1/2} \quad (7)$$

Where M is the number of random measurements in CS scenario, and E is commuted as [10]:

$$E = 1/M\sum_{n=1}^{M}E_s[n] \quad (8)$$

In the PFS step the peak clipping is employed to minimize deviation between the detective peaks of the ECG signal. Then, the energy threshold is proposed as [11]:

$$E_{th} = \begin{cases} E_s \text{ if } E_s \le A_T \\ 0 \text{ otherwise} \end{cases} \quad (9)$$

The peak clipping adaptive threshold is illustrated as [12]:

$$P_T = 0.1 \times \max(E_{TH}) \quad (10)$$

Then, the peak clipping is performed with the following equation [13]:

$$P_C = \begin{cases} E_{TH} \text{ if } E_{TH} \le P_T \\ P_T \text{ otherwise} \end{cases} \quad (11)$$

In the SET step, the Shannon Energy (SE) OF the normalized ECG is determined as [14]:

$$SE = -ecg[n] \;\; \log(ecg[n])^2 \quad (12)$$

The average value of the filtering is adjusted based on the SE values to determine the approximate location of the parts 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.

IV. SIMULATION RESULTS

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 (MITADB) which sampled at 360 Hz with 11-bit resolution. The Sensitivity Percentages (SP), Positive Prediction Percentages (PPP), and Detection Accuracy Percentages (DAP) are employed to determine the validation of the proposed algorithm. The sensitivity can be expressed as:

$$SP\% = (P_T / P_T + N_F) \times 100 \quad (13)$$

Where P_T and N_F are the number of true-positive part and the number of false-negative parts respectively. The positive prediction is obtained of the following equation:

$$PPP\% = (P_T / P_T + P_F) \times 100 \quad (14)$$

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

$$DAP\% = (P_T / P_T + P_F + N_F) \times 100 \quad (15)$$

The simulation results for records 105,108,200,203 and 205 are given in the Table 2.

Table 2: 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 3 compares the performance of the proposed algorithm with the EMD –based method (Empirical Mode Decomposition). While the EMD-based method does not achieve perfect detection when the ECG signal has narrow and wide QRS segment, the proposed algorithm allows better detection rate even when ECG signals contain narrow and wide QRS segments.

Table 3: 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 the Table 3 the proposed algorithm illustrates better detection accuracy, specifically for abnormal ECG records.

Table 4 compares EMD-based method and the proposed algorithm regarding their SP and PPP and shows significantly better SP and PPP for the proposed algorithm.

Table 4: 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 2 illustrates the SP of of the selected ECG records and obtained by EMD-based and the proposed algorithm.

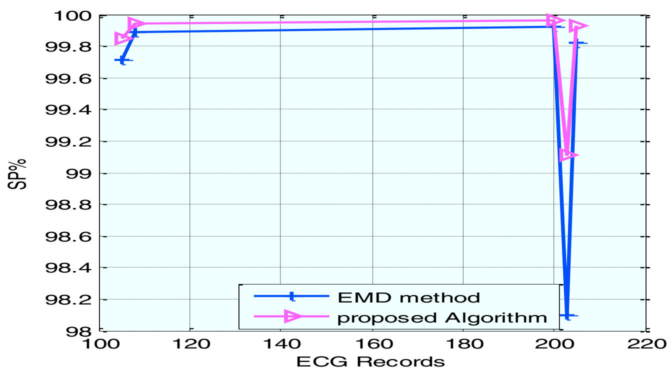

Fig.2: Comparing the SP of EMD-based method and the proposed algorithm

As depicted in Fig. 2 sensitivities of received ECG signal are increased by the proposed algorithm. This ability allows achieving better performance of wireless ECG systems based on CS theory. Figure 3 demonstrates the PPP in terms of selected ECG records and compares it for EMD-based method and the proposed algorithm.

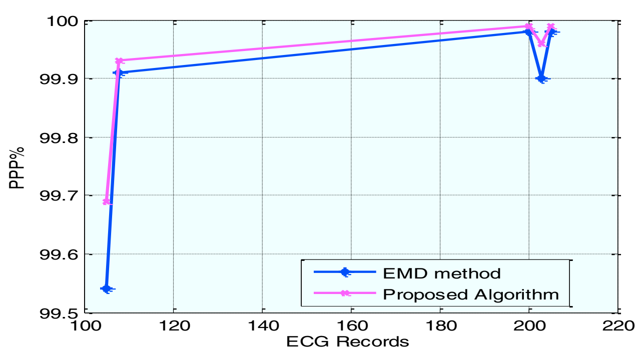

Fig.3: The comparative work on PPP in the EMD-based and proposed algorithm

As it can be seen in Fig. 3, the proposed algorithm shows an increase in the prediction level at gateways or access points for wireless ECG systems. The simulation result illustrates satisfying quality of prediction level for wireless ECG systems with CS theory. This ability allows providing the detection algorithm with high probability.

V. CONCLUSION

The novelty of this paper has focused on the collaboration form CS theory, PFS, and SET algorithms to establish new detection algorithm for wireless ECG signals at gateways and access points with high probability and high accuracy at hospitals or medical centers for diagnostic and therapeutic purposes. The proposed algorithm has consisted of filtering, Shannon energy transformation, and peak clipping steps. The simulation results show that the proposed algorithm achieves better detection rate in comparison with EMD-based method. As expected, our simulation results illustrate an increment of 0.1% for sensitivity as well as 1.5% for the prediction level and a good level of quality for detection accuracy. The wireless ECG systems based on the proposed algorithm give patients greater mobility and increased comfort by freeing them from the need to be connected to hospital equipments.

VI. FUTURE WORK

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

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