Wireless ECG systems with New Sampling-rate Approach Based on Compressed Sensing Theory

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Abstract— The main drawback of current ECG systems is the location-specific nature of the system due to the use of fixed/wired systems. The currently ECG systems are also restricted by size, patient's mobility, power, and transmission capacity. Therefore, the currently ECG systems need to be further developed in order to achieve extended mobility and wireless monitoring of several patients at the same time. The wireless ECG systems provide vital information about the heart to physicians and doctors at anytime and anywhere by removing constraints of time and location of patients while increasing both the mobility and the quality of healthcare systems. With this in mind, Compressed Sensing (CS) procedure and the collaboration of Block Sparse Bayesian Learning (BSBL) framework is used to provide a robust low sampling-rate approach for wireless ECG systems. Advanced wireless ECG systems based on our approach 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. Our simulation results illustrate 15% reduction of Percentage Root-mean-square Difference (PRD) for a selected recode of ECG signals. The simulation results also show that sampling-rate can be minimized to 35% of nyquist-rate.

Index Terms- Sampling-rate, Signal-to-noise ratio, Wireless ECG Systems, Compressed Sensing, Block Sparse Bayesian learning

I. INTRODUCTION

The wireless healthcare systems are expected to provide a breakthrough technology in healthcare areas such as electronic health, home care, telemedicine, and physical rehabilitation. To expand the applications of wireless healthcare systems to Electronic Health (EH), Mobile Health (MH), and Ambulatory Health Monitoring Systems (AHMS) the power consumption and sampling rate should be kept a minimum value. On the other hand, WBANs are one area that has not yet experimented with the benefit that CS theory might provide. 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 [1]. The traditional approaches have two important drawbacks. First, they generate huge samples for many applications with large bandwidth that is not tolerated. Second, even for low signal bandwidths such as ECG signals, they produced a large amount of redundant digital samples [2].

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That is why it is desirable to reduce the number of acquired ECG samples by using advantages of the sparsity. 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 the original signal from a small number of random measurements. Therefore, the fundamental contribution of this paper is to establish low sampling-rate algorithm based on CS theory and the BSBL framework to establish low sampling-rate approach for wireless ECG systems due to the lake of research in this field. The wireless ECG systems with CS approach and the collaboration from BSBL framework can offer two important advantages compared to current health monitoring systems. The first advantage is the mobility of patients due to use of ambulatory health monitoring systems. Second advantage is to control and investigate ECG signals from outside of hospital and medical centers in order to increase an ability of prevention and early diagnosis. By this convenient means, elderly people can keep track of their health conditions on their Smart phones or any portable device without the frequent visit to their doctor's offices [3]. The wireless ECG signals based on our new sampling procedure provide low data rate, very small transmitting power requirement, and longer battery life and also serve the goal of reducing healthcare costs because of monitoring several patients simultaneously. The contribution of this paper lies in the use of our new algorithm to minimize PRD. The simulation results indicate that good level of quality of sampling-rate can be achieved when *PRD* decreases by 15%. The simulation results also show that sampling-rate can be minimized to 35% of nyquist-rate**.** The structure of this paper is organized as follows: Section II gives an overview about CS theory in general and specifically for WBANs. Section III proposes our new algorithm based on collaboration of CS theory and BSBL framework. The reminder of the paper is categorized in the following way: the simulation results, including results on *SNR* and *PRD* are presented in Section IV. Section V offers main contribution of this work and relation to prior work. The conclusion is drawn in Section VI.

II. Background of Compressed Sensing

The CS is believed to have strong advantages, which are promising for Wireless health care systems. Our goal in the digital-CS theory as a new sampling scheme is to reduce the load of sampling-rate by decreasing the number of samples after the Analog to Digital Convertor (ADC) required to completely describe a signal by exploiting its compressibility [4]. An important aspect of CS theory is that our measurements are not point samples but more general linear functional of the signals [5]. Figure 1 shows CS in wireless healthcare systems.

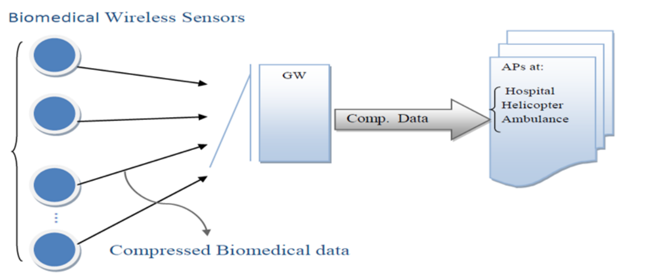

Fig.1. CS in wireless healthcare systems

As it is depicted in Fig., 1 biological date is collected by biomedical wireless sensors, and the compresed data are then transmitted to Acess Points (APs) via Gate Ways (GWs) in the hospital and medical centers for diagnostic and therapeutic purposes. Figure 2 illustrates the fundamental architecture for CS theory.

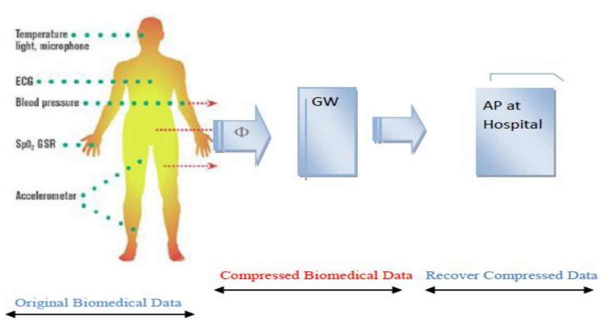

Fig.2: Architecture of CS

In the CS scenario, a compressible or sparse signal $Y \text{ in } \mathbb{R}^N$ transfers to compress signal $\mathbb{C}$ in $\mathbb{R}^M$ such that $M \ll N$ and can be expressed like [6], [7]:

$$\begin{pmatrix} \mathbb{C}_1 \\ \vdots \\ \mathbb{C}_M \end{pmatrix} = \begin{pmatrix} \Phi_{11} & \cdots & \Phi_{1N} \\ \vdots & \vdots & \vdots \\ \Phi_{M1} & \cdots & \Phi_{MN} \end{pmatrix} \begin{pmatrix} Y_1 \\ \vdots \\ Y_N \end{pmatrix} \tag{1}$$

Thus, CS scenario has two important steps. First step in CS offers a stable measurement matrix $\Phi_{M\times N}$ to ensure that the salient information in any compressible signal is not damaged by the dimensionality reduction from $D \in \mathbb{R}^N$ down to $\mathbb{C} \in \mathbb{R}^M$. In the second step, the CS theory offers a reconstruction algorithm under certain condition and enough accuracy to recover original signal Y from the compressed signal. Therefore, we can exactly reconstruct the original signal Y with high probability via ℓ_1 norm. The condition which guarantees the correctness of this recovery is given like:

$$M \geq cK \log(N/K), \tag{2}$$

Which c is constant and M is the number of random linear measurements [7]. To guarantee the robust recovery with high probability and enough accuracy, the random dictionary matrix Φ must have RIP property [8]. This property provides theoretical grantees to recover K-sparse using a system of M linear equations with K unknowns. That is why the random dictionary matrix Φ must verify the following conditions:

$$(1-c)\,\|\Phi_S y\|_2^2 \leq (1+c)\,\|y\|_2^2\,, \tag{3}$$

where Φ_S is a sub-matrix of matrix $\Phi_{M\times N}$ with $S \leq M$, y is a given vector, and c is constant [9]. Our simulation results show that by employing the CS, the wireless healthcare systems can achieve a higher transmission, a lower time delay and higher probability of success of data transmission. Therefore, a combination of CS theory to wireless healthcare systems is an optimal solution for achieving robust wireless healthcare systems with low sampling rate and power consumption [10, 11].

III. Proposed Approach

The BSBL framework is partitioned the ECG signal into a concatenation of non-overlapping blocks, and a few of blocks are non-zero [12]. More specifically, the number of non-zero blocks is the same as the number of random linear measurements in CS approach. This approach can prune out blocks in abnormal ECG signals [13]. The Structural Similarity Index (SSI) and Percentage Root-mean-square Difference (PRD) are employed as performance measures in our approach. The SSI metric is defined as [13]:

$$SSI = (\mathbb{C}/\mathrm{Y}) \times 100\,, \tag{4}$$

Where Y and $\mathbb{C}$ are the original and recovered ECG signals respectively. This metric measure the similarity between the recovered and original ECG signals [14]. Higher *SSI* means better recovery quality. Our simulation results will show the proposed approach has this ability to achieve *SSI* with value close to 100%. The PRD is computed as [14]:

$$PRD = (\|Y - \mathbb{C}\|_2 / \|Y\|_2) \times 100\,. \tag{5}$$

The value of *PRD* shows the quality of reconstruction approach. The relationship between the measured *PRD* and diagnostic distortion is recognized on the weighted diagnostic data for ECG signals, which classifies the different values of *PRD* based on the signal quality obtained by a specialist. Table 1 illustrates the resulting different quality classes and corresponding *PRD* values. As depicted in Table 1, lower *PRD* means better recovery quality.

Table1: Different Quality Classes

PRD	Quality of recovery
$0 \sim 1\%$	Excellent
$1 \sim 2\%$	Very good
$2 \sim 0.85\%$	Good
$\geq 0.85\%$	Poor

Table 1 illustrates the entire algorithm based on CS theory and BSBL framework.

Table 1: Proposed Reconstruction Approach

Algorithm : Reconstruction Approach
Require: Matrix $[\Phi]$, $i = 0$
1: Generate initial $[\mathbb{C}]_0 = [\Phi]_0[Y]$.
2: Find C_0 by solving $C_0 = \arg\min_C \|\| \mathbb{C} - \Phi_0 C \|\|_1^2$
3: Calculate the following features: $R_0 = \mathbb{C} - \Theta_0 C_0, CR_0 = R_0 / \mathbb{C},$ $PRD_0 = \|\| R_0 \|\|_2 / \|\| \mathbb{C} \|\|_2$
4: If $C_0 - \mathbb{C}_0 = 0$ the reconstruction accuracy is fine.
5: While $C_0 - \mathbb{C}_0 \geq 0$
6: $i = i + 1$
7: Solve $C_i = \arg\min_C \|\| \mathbb{C} - \Phi_i C \|\|_1^2$
8: Calculate the following features: $R_i = \mathbb{C} - \Phi_i C_i, CR_i = R_i / \mathbb{C}, PRD_i = \|\| R_i \|\|_2 / \|\| \mathbb{C} \|\|_2$
10: end while
11: provide final matrix $[\mathbb{C}]$
12: End Reconstruct Algorithm

IV. Simulation Results

In this Section, features of ECG signals such as Compression Ratio (*CR*), *SNR*, and *PRD* are simulated. The following assumptions were made for simulation:

► Experiments are carried out over a 10-minutes ECG signal from MIT-BIH database [15].
► One hundred repetitions are averaged for our simulation results. To validate the simulation results ECG signals from records 100,108,115 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.

$$SNR = -20\log_{10}(0.01PRD). \tag{9}$$

►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 nonzero entries equal to $\pm 1/\sqrt{2}$ is used for sparse binary matrix.
►The permissible parameters were adopted of IEEE802.15.3, IEEE802.15.5, and IEEE802.16e protocols which support low power communication in WBANs [14].
►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:

$$\min_{c\in\mathbb{R}^N} \|c\|_1 \quad \text{subject to} \quad \mathbb{C} = \Phi Y. \tag{10}$$

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

$$\arg\min_{c\in\mathbb{R}^N} \|c\|_1 \text{ subject to} \|\mathbb{C} - \Phi Y\|_p \text{ for } p \geq 2. \tag{11}$$

►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 in order to simulate Signal-to-Noise Ratio (SNR). Figure 1 compares the output PRD, averaged over-all database records for a given ECG signal in non-CS and CS scenarios. Figure 1 illustrates that CS approach exhibits excellent robustness with respect to random binary sensing matrix, unlike non-CS method. To compare PRD, random binary sensing matrix is applied to all the records of the MIT-BIH ECG database, and the output PRD is measured. Figure 3 shows the simulation result only for record of 108 from the database in non-CS and CS theory scenarios.

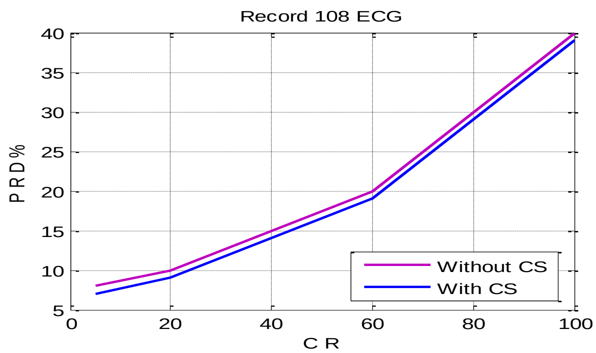

Fig.3: ECG record 108 with CS and non-CS scenarios

Figure 4 illustrates the sampling-rate for a particular ECG signal in terms of Compressed Ratio (CR=N/M).

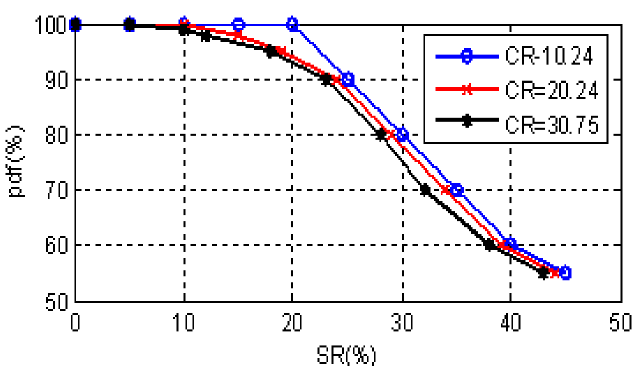

Fig.5: Probability of detection ECG signals versus SR

As depicted in Figure 4, the sampling rate can be reduced 35% of nyquist-rate without sacrificing the performance which is the probability of detection of ECG signals.

VI. Conclusion

This paper has proposed a modified sampling approach for normal and abnormal ECG signals based on CS theory and the collaboration from BSBL framework. As expected, the proposed algorithm exhibits better performance on *SNR*, *CR*, and *PRD*. Our simulation results indicate that good level of quality of *CR* can be achieved when *PRD* decreases by 15% and *sampling-rate* minimizes to 35% of nyquist-rate by employing the CS theory.

VII. Future Work

We have examined the benefit of CS theory and BSBL framework for one record of normal and non-normal ECG signals. Our future work involves developing the CS theory and BSBL framework for other records of ECG signals.

References

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

[2] M. Balouchestani, K. Raahemifar and S. Krishnan, "Low power wireless body area networks with compressed sensing theory," in *Circuits and Systems (MWSCAS), 55th IEEE International Midwest Symposium on*, 2012, pp. 916-919.

[3] A. S. Alvarado, C. Lakshminarayan and J. C. Principe, "Time-Based Compression and Classification of Heartbeats," *Biomedical Engineering, IEEE Transactions on*, vol. 59, pp. 1641-1648, 2012.

[4] 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 Eighth International Conference*, pp. 1-4.

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

[6] S. Atapattu, C. Tellambura and Hai Jiang, "Performance of an Energy Detector over Channels with Both Multipath Fading and Shadowing," Wireless Communications, *IEEE Transactions*, vol. 9, pp. 3662-3670, 2010.

[7] P. K. Baheti and H. Garudadri, "An ultra low power pulse oximeter sensor based on compressed sensing," in *Wearable and Implantable Body Sensor Networks, 2009. BSN 2009. Sixth International Workshop on*, 2009, pp. 144-148.

[8] A. M. R. Dixon, E. G. Allstot, A. Y. Chen, D. Gangopadhyay and D. J. Allstot, "Compressed sensing reconstruction: Comparative study with applications to ECG bio-signals," in *Circuits and Systems (ISCAS), 2011 IEEE International Symposium*, pp. 805-808.

[9] Hyejung Kim, R. F. Yazicioglu, P. Merken, C. Van Hoof and Hoi-Jun Yoo, "ECG Signal Compression and Classification Algorithm With Quad Level Vector for ECG Holter System," *Information Technology in Biomedicine, IEEE Transactions* , vol. 14, pp. 93-100, 2010.

[10] S. M. Jadhav, S. L. Nalbalwar and A. Ghatol, "Artificial neural network based cardiac arrhythmia classification using ECG signal data," in *Electronics and Information Engineering (ICEIE), 2010 International Conference*, pp. V1-228-V1-231.

[11] H. Mamaghanian, N. Khaled, D. Atienza and P. Vandergheynst, "Compressed Sensing for Real-Time Energy-Efficient ECG Compression on Wireless Body Sensor Nodes," *Biomedical Engineering, IEEE Transactions*, vol. 58, pp. 2456-2466, 2011.

[12] L. F. Polania, R. E. Carrillo, M. Blanco-Velasco and K. E. Barner, "Compressed sensing based method for ECG compression," in *Acoustics, Speech and Signal Processing (ICASSP), 2011 IEEE International Conference*, pp. 761-764.

[13] W. Dullaert, H. Rogier, L. De Camillis and T. Dhaene, "Improving link quality of UWB communication links by means of PSWF-basis persuit denoising," in *Antennas and Propagation in Wireless Communications (APWC), 2011 IEEE-APS Topical Conference*, pp. 126-129.

[14] A.Chacko and S. Ari, "Denoising of ECG signals using empirical mode decomposition based technique," in *Advances in Engineering, Science and Management (ICAESM), International Conference on*, 2012, pp. 6-9.

[15] C. Ye, B. V. K. Vijaya Kumar and M. T. Coimbra, "Heartbeat Classification Using Morphological and Dynamic Features of ECG Signals," *Biomedical Engineering, IEEE Transactions on*, vol. 59, pp. 2930-2941, 2012.