ISSN (Online) 2394-6849

International Journal of Engineering Research in Electronics and Communication Engineering (IJERECE)
Vol 4, Issue 6, June 2017

DWT based Joint Compressive Sensing and Recovery of MECG Signals

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Abstract: **Remote Health Monitoring is emerging as the smart healthcare solution due to the technological breakthroughs in bio-medical field. One such promising health care application is ECG monitoring to detect cardiac diseases. This is made possible through Wireless Body Area Network (WBAN) which consists of wearable intelligent sensor nodes on human body. These nodes are responsible for acquiring and sending the signals to healthcare centres. Huge data is difficult to store as well as to transmit over energy constrained sensor nodes. Energy-efficient compression techniques offer promising solutions to overcome these drawbacks. The algorithms uses joint compression of Multi-channel ECG (MECG) signals through compressive sensing and joint reconstruction by solving convex optimization problem through Mixed Norm Minimization (MNM). Two channel ECG signals are collected from MIT-BIH Arrhythmia database record 100. Discrete Wavelet Transform is applied for both channels to make signals sparse. Sparse Signals are jointly compressed using sensing matrix and are jointly reconstructed using MNM. Matlab simulation shows good reconstruction quality of 2-channelECG signals with PRD of 0.60 and 0.53 for channel 1 and channel 2 respectively.**

***Keywords*--WBAN,Discrete Wavelet Transform (DWT), Joint Sparsity, Mixed Norm Minimization (MNM)**

I. INTRODUCTION

Smart remote health care solutions are boon to patients suffering from long term illness as well as for elderly patients who require continuous monitoring. Remote monitoring offers healthcare solutions which are economical and convenient for patients [3]. This has become possible because of the technological growth which has constantly miniaturized the electronic devices andwireless networks which revolutionized the communication.

With this, Wireless Body Area Networks (WBANs) emerged as bio-medical technology which offers health monitoring withthe help of non-invasive intelligent sensors placed on the body or implanted inside body[1].Now-a-days wearable sensors are capable of sensing as well as processing number of physiological signals and sending them in real-time to healthcare centres through hi-speed wireless networks for early detection and monitoring. Recent years, improper life style and stress has increased the risk of heart diseases. Hence physiological ECG sensorhas become immensely popular and has opened doors to extensive research to make mHealth (Mobile Health)real.

ECG sensor measures the electrical activity of the heart over a time period. Each beat of the heart is triggered by an electrical impulse normally generated from special cells in the upper right chamber of the heart [2]. As these electrical signals travel through the heart are recorded and doctors diagnose heart condition looking at the patterns. Constant monitoring creates huge amount of data which poses challenge for energy constrained sensornodes to store and transmit them over energy hungry wireless links to medical centres. In order to overcomethese limitations, there is a need of energy-efficient, low-complexity data compression technique.

In traditional data acquisition context, signals are first sampledfollowing well-known Shannon's theorem which says that to ensure accurate reconstruction; the signal must be sampled at Nyquist Rate. The sampling rate must be at least twice the maximum frequency present in the signal. After signal is sampled, various compression techniques are often used to reduce the amount of data. This process is wasteful of resources sincemost of the information acquired during sampling stage is removed in compression stage. Instead one can acquire the signal with only the information which is of interest. This concept is called Compressive Sensing. Compressive Sensing has opened new era in digital signal processing applications offering efficient data compression method.

II. COMPRESSIVE SENSING THEORY

The process of compressive sensing enables accurate recovery of the signal even though just few measurements are acquired, if two important requirements are met. They are Sparsity and Incoherence [4].

A. Sparsity

Sparsity refers to the matrix or vector containing fewest non-zero entries. The input signal should be sparse when expressed in the proper transform basis. Sparse signal refers to the signal with most of elements zero and most of information lies with few non-zero elements. Transform basis are application dependent. This sparsity domain is represented as [ψ].

B. Incoherence

The sparsity domain [ψ] and sensing matrix [ϕ] should be incoherent with each other. This means that the correlation between sparsity domain and sensing matrix must be small [5]. The correlation is defined as,

$$\mu(\psi,\phi) = \sqrt{N}\max_{1\le k,j\le N}\left|\langle\phi_k,\psi_j\rangle\right| \quad (1)$$

The compressed signal [Y] for input signal [X] is given by,

$$O = \phi I \quad (2)$$

Where, $I = \psi C$, ψ is the sparsity domain and φ is the sensing matrix.

$$O = \phi\psi C = \Theta C \quad (3)$$

Now this equation is the ill-posed linear inverse problem [5]. Signal should be extracted from small number of samples; hence the equation becomes under-determined and has many possible solutions. Therefore, solving such equation is NP hard. But since we want to recover sparse signal, sparsest solution can be obtained by solving convex optimization problem.

III. JOINT COMPRESSION OF MECG

In real time, ECG measuring is done via multiple leads for detailed diagnosis of patients. Hence ECG signals are recorded in twelve lead forms. These Multi-channel ECG signals are not independent since these are from different projections of the same source. Hence there is correlated information across these channels.

1) Joint Sparsity

Multi-channel ECG signals share common sparsity profile when represented in the transform domain [10]. Therefore, if we stack these multi-channel transform coefficients as columns of a matrix, the resulting matrix will have row sparsity [8]. This means, the information across multiple channels gets confined to few non-zero rows exhibiting joint sparsity. Hence, multi-channel coefficients are jointly compressed using single sensing matrix.

2) Discrete Wavelet Transform

Discrete Wavelet Transform (DWT) has emerged as one of the powerful tools which make ECG signal to have sparser representation. Using wavelet transforms it is possible to analyse signal in both time as well frequency domain. DWT offers good time resolution at high frequencies and good frequency resolution at low frequencies [6]. Wavelet Transform uses shorter windows at high frequency and longer windows at low frequency which is in contrast to Short-Time Fourier Time (STFT) which uses a single analysis window. DWT is the most suitable because of the time-varying property of the ECG signal.

3) Sensing Matrix

Most of the random matrices are highly incoherent with fixed sparsifying basis with high probability [7]. The number of rows of sensing matrix gives us the number of measurements which we want to consider. The number of columns must be equal to the number of rows of signal vector. When multi-channel ECG are compressed using single sensing matrix, multiple vectors are produced which are called as Multiple Measurement Vectors (MMV).

4) Joint Compressive Sensing

Let $I = (i_1, i_2, i_3 \ldots. i_L) \in R^{N*L}$ be the signal data matrix where L represents channels of MECG and N represents the length of each channel. Single wavelet basis for all the channels is represented by $\Psi = (\psi_1, \psi_2, \psi_3 \ldots. \Psi_N)$ where $C = (\alpha_1, \alpha_2, \alpha_3 \ldots. \alpha_L) \in R^{N*L}$ represents matrix with wavelet coefficient vectors from all the channels. Therefore, $O = \Psi S$ represents MECG in transform domain. Then, compressed multiple measurement vectors of MECG channels is given by,

$$O = \Phi I \quad (4)$$

Where $O = (o_1, o_2, o_3 \ldots. o_L)$ represents compressed vectors from L channels, $\Phi \in R^{M*N}$ represents sensing matrix used. Sparse binary random matrices are the universal good choice as it consumes less memory to store [9]. The compressed MMV Q in equation (4) exhibits joint sparsity. The equation (4) is the ill-posed linear inverse problem and can be cast as a linear programming problem.

IV. JOINT RECOVERY VIA MNM

Given compressed measurements C and signal is known to be sparse in priori, solution to equation (4) is possible since it is a convex optimization problem. Since the signal is known to be sparse, finding sparsest possible solution will accurately reconstruct the original signal at the receiver.

For efficient recovery of the sparse solution, we want a convex function which can measure sparsity. L_1- norm optimization possesses the ability to recover sparse solutions using L_1 – norm by solving optimization problem. L_1 – norm promotes sparse solutions and it is capable of producing solution with few large coefficients where as L_2 – norm gives solutions with non-sparse coefficients. Here, mixed norm minimization involving L_1 and L_2 norms are used to jointly recover row sparse coefficients [11]. The joint recovery of row sparse coefficients using Mixed-Norm Minimization (MNM) based convex optimization problem given by,

$$\min \|C\|_{p,q} \text{ such that} \|O - \Theta C\|_F \le \varepsilon \quad (5)$$

Where ε is the noise tolerance limit and $\|.\|_F$ is theFrobenius norm. $\|C\|_{p,q}$ represents the mixed-norm $\ell_{p,q}$ of the coefficient matrix C and is given by,

$$\|C\|_{p,q} = \left(\sum_{j=1}^{N} \|C^{\rightarrow j}\|_p^q\right)^{\frac{1}{q}} \tag{6}$$

Mixed norm refers to sum of L_2 – norm of each row of A which promotes only few rows selection. First L_2– norm where p=2 is used over rows which gives dense solutions. Now, sparsity is induced at right places by using L_1 – norm. Hence non-zero coefficients of all the channels are grouped together acting as a group sparsity inducing norm. Sparsity is induced by L_1 – norm on the dense coefficients obtained after taking L_2 –norm on each row helps in the recovery of row-sparse solution. $L_{2,1}$– mixed norm is used with p=2 and q=1 which gives row-sparse solution vectors since it exploits row-sparsity of MECG signals [12].

A. Algorithm Steps

1) Initialize parameters with window length N, number of measurements M and ε = 0.2
2) Load the MECG signals from MIT-BIH Arrhythmia database
3) Apply multi-level wavelet decomposition for all the channels
4) Use single sensing matrix to jointly compress MECG wavelet coefficients
5) Obtain compressed signal
6) Solve MNM based convex optimization problem to recover wavelet coefficients from all the channels
7) Recover the time-domain signal by applying Inverse Discrete Wavelet Transform (IDWT)

V. SIMULATION RESULTS

Two-channel ECG signals of 1-minute long from MIT-BIH Arrhythmia database with 4096 samples of record no 100, 101, 104, 108, 109 and 111 are evaluated. The window length is N=512. Daubechies wavelets 'db1' are used as the sparsity domain. 5-level wavelet decomposition is performed for all the channels. Binary Sensing Matrix with d (d=12) number of 1's at random places in each column is used. Number of measurements selected is M=192.

CVX is an open source MATLAB based modelling package to solve convex optimization problems [13]. CVX toolbox is used to solve equation (6) to recover the both the channels of ECG signal.Matlab version R2015b software [14] is used for the simulation.

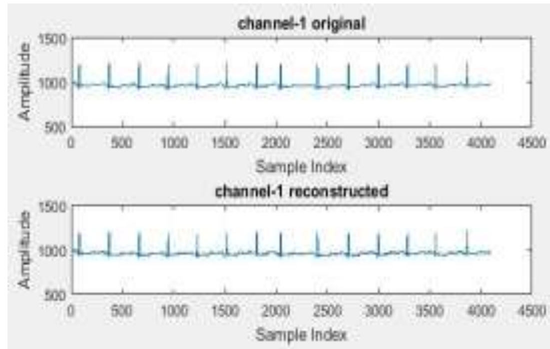

Figure1: Original and Reconstructed ECG signal for Channel-1

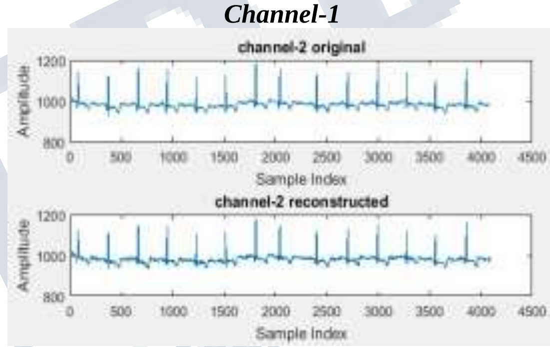

Figure 2: Original and Reconstructed ECG signal for Channel-2

Figure 1 shows original and reconstructed ECG for channel-1. Figure 2 shows original and reconstructed ECG for channel-2. Channel-1 and channel-2 refers to two leads ML II and V5 respectively from MIT-BIH database Record No. 100.

A) Performance metrics

The evaluation of the algorithm is performed based on important parameters which help us in understanding the performance and measuring quality allowing the scope for improvement.

Compression Ratio (CR):

It is defined as the number of bits required to represent original signal to compressed signal. This is used to measure the data reduction ability of the algorithm and is given as:

$$CR(\%) = \frac{B_{original} - B_{compressed}}{B_{original}} \times 100 \tag{7}$$

Percentage-Root mean square Difference (PRD):

PRD is used to measure the distortion calculation between original and reconstructed signal. It is defined as:

International Journal of Engineering Research in Electronics and Communication Engineering (IJERECE)
Vol 4, Issue 6, June 2017

$$PRD(\%) = \left(\frac{\| I - \hat{I} \|_2}{\| I \|_2} \right) \times 100 \quad (8)$$

Table 1: PRD and CR for Channel-1 and Channel-2 for different MIT-BIH recordings

Record No.	PRD channel-1	PRD channel-2	CR
100	0.6003	0.5045	62.5
101	0.7825	0.3767	62.5
104	0.9369	0.8716	62.5
108	0.6956	0.8007	62.5
109	1.3462	1.0162	62.5
111	0.8557	0.6813	62.5

VI. CONCLUSION AND FUTURE SCOPE

ECG signal acquisition in remote health monitoring application generates huge data which poses challenge to the resource constrained sensor nodes. Therefore, such system requires robust data compression algorithm. In practice, ECG signal is acquired through multiple leads and channel-by-channel processing is not ideal choice in real time processing. In this paper, joint compression and recovery of MECG signal via MNM is presented. Evaluation ofperformance on 2-channel MIT-BIH database metric shows very good reconstruction quality for both the channels. Efficient recovery requires ECG signal to have sparser representation and ensuring good incoherence between both sparsity and sensing basis. Future scope of this work is to use sparse binary sensing matrix which satisfies high incoherence property.

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