Application of Compressed Sensing (CS) for ECG Signal Compression: A Review

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Abstract Compressed Sensing (CS) is a fast growing signal processing technique that compresses the signal while sensing and enables exact reconstruction of the signal if the signal is sparse with a few numbers of measurements only. This scheme results in reduction of storage requirement and low power consumption of system compared to Nyquist sampling theorem, where the sampling frequency must be at least double the maximum frequency present in the signal for the exact reconstruction of the signal. This paper presents an in-depth study on recent trends in CS focused on ECG compression. Compression Ratio (CR), % Root-mean-squared Difference (% PRD), Signal-to-Noise Ratio (SNR), Root-Mean Square Error (RMSE), Sparsity and power consumption are used as the performance evaluation parameters. Finally, we have presented the conclusions based on the literature review and discussed the major challenges in CS ECG implementation.

Keywords Compressed sensing (CS) · ECG compression · SPIHT · Sparsity

1 Introduction

Electrocardiogram (ECG) is an important and advanced diagnostic tool used for various heart diseases diagnosis, such as arrhythmia, myocardial ischemia, and cardiac infarction. The detail interpretation provides information about patient's health. The different heart activities are represented by different waves. A normal ECG includes a P wave followed with QRS complex wave and lasts with T wave.

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Figure 1 shows the normal ECG waveform. The P wave is caused produced by the depolarization of the atria muscles and associated with their contraction, while the QRS complex wave is initiated by the depolarization of ventricles before to their contraction. The detection of the QRS complex is an important step in automated ECG analysis. Because of their distinctive shape, the QRS complex used as the reference tip for automated heart rate monitoring and as the initial point for additional evaluation.

Therefore, the long-term ECG data records become an important aspect to perceive information from these heart signals, resulting in increase in memory size of data. Hence, the ECG data compression becomes an essential for decreasing the data storage and the transmission times. ECG compression methods are categorized into two main groups: (i) Direct compression methods (ii) Transform compression methods. In the transform methods, the discrete wavelet transform-based techniques are simple to implement and provides good localization in both time and frequency scale.

The further best work in this area is described by embedded zero tree wavelet (EZW) [1] and a set partitioning in hierarchical tree (SPIHT) [2, 3] protocols, which work on the self similarity basis of the wavelet transform.

Compared to traditional ECG compression scheme, CS [4, 5, 6] transfers the computational load from the encoder side to the decoder side, and thus provides simple encoder hardware implementations. Also, there is no need to encode locations of the significant wavelet coefficients. This paper presents the detailed review of different aspects of CS-based ECG compression. The paper is outlined as: Sect. 2 describes the CS acquisition and recovery model. Section 3 presents different performance measures of signal. In Sect. 4, we have presented the detailed literature reviews on current CS-based ECG compression followed by conclusions in Sect. 5.
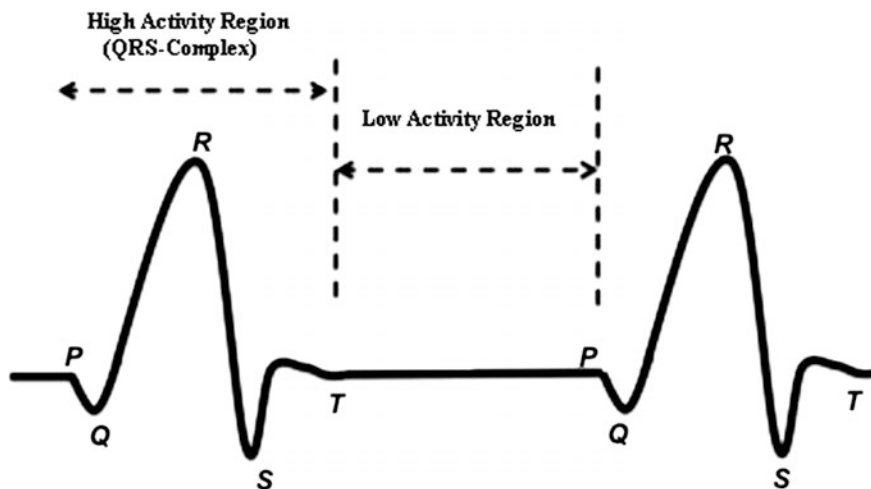

Fig. 1 Normal ECG waveform

2 Compressed Sensing (CS) Framework

2.1 Background

CS is a fast developing signal compression technique that acquires the signal and exactly recovers with few numbers of samples than Shannon–Nyquist sampling. CS takes advantage of signal sparsity property in some domain like wavelet transform. Nyquist sampling depends on the greatest amount of rate of alteration of a signal, whereas CS depends on the greatest amount of rate of knowledge in a signal. The CS executes two main operations: compression and recovery of signal.

2.2 CS Sensing Model

Compressed sensing scheme is represented as follows:

$$y = \Phi f \tag{1}$$

where, f is the original input signal of length $N \times 1$, y is the compressed output signal of length $M \times 1$, and Φ is the $M \times N$ sensing matrix. Here, as Φ is always constant, CS is nonadaptive scheme.

The input signal x is further defined as

$$f = \Psi_x \tag{2}$$

where, x is the nonsparse input signal with length N and Ψ is the $N \times N$ sparsifying basis. Combined form of Eqs. (1) and (2) as follows:

$$y = \Theta_x \tag{3}$$

where, $\Theta = \Phi\Psi$ is commonly referred to as the sensing matrix. CS acquires $M << N$ observations from N samples utilizing random linear estimate. In order to implement a CS algorithm correctly, there are three key requirements:

(a) The input signal f must be a sparse in some domain.
(b) The Ψ and Φ must be incoherent.
(c) The Φ should satisfy the Restricted Isometric Property (RIP) [7] and defined as

$$(1 - \delta_s) \|f\|_2^2 \leq \|\Theta f\|_2^2 \leq (1 + \delta_s) \|f\|_2^2 \tag{4}$$

For exact and stable compression, and signal recovery, Candes et al. [8, 9] recommends a minimum number of compressed measurements (m) based on the sparsity and coherence constraints outlined.

$$m \geq c. \, \mu^2(\Psi, \Phi)s. \log(N) \tag{5}$$

where, s is number of nonzero elements and c is a small fixed value. The sensing matrix can be designed with random distribution [10] values from Bernoulli, Gaussian, and uniform probability density functions.

2.3 CS Signal Reconstruction Model

Because Φ is not a square matrix, this CS problem becomes under determined problem with many possible solutions. These CS recovery algorithms require information of a representation basis where the signal is compressible or sparse for approximate or accurate recovery of signal. Reconstruction algorithms in CS exploit the sparse solution by minimizing L0, L1, L2 norm over solution space. L0-norm minimization will accurately reconstruct the original signal under the sparse condition, with slow speed and is NP (Non-Polynomial) hard. The L2-norm minimization is fast but it does not find the sparse solution resulting in error. The L1-norm gives exact sparse solution with efficient reconstruction speed. Hence, L1-norm is the good alternative to L0-norm and L2-norm minimization to find the accurately sparse solution. Finally, original signal can be reconstructed by calculating x using L1 norm minimization as given by equation below:

$$\min \|\hat{x}\|_1 \text{ Subject to } y = \Theta\hat{x} = \Psi\Phi\hat{x} \tag{6}$$

The sparsity and incoherence conditions guarantee the high probability of sparse exact solution using Eq. (6).There are different CS reconstruction algorithms available based on convex optimization method for e.g. Basis Pursuit (BP) [11], BP denoising (BPDN) [11], M-BPDN [12], LASSO [13] and greedy methods like OMP [14, 15], CoSaMP [16].

3 Performance Evaluation Parameters

There are different distortion measures used for performance evaluation of signal like % root-mean squared difference (PRD), Compression ratio (CR), Root-mean square error (RMS), Signal-to-noise ratio (SNR), and sparsity.

3.1 Percentage Root-Mean Squared Difference (PRD)

PRD is the measure of the difference between the input signal and recovered signal and given as:

$$PRD(\%) = \frac{\sum_{n=1}^{N} \left(f(n) - \hat{f}(n) \right)^2}{\sum_{n=1}^{N} f^2(n)} \tag{7}$$

Measurement of PRD without the DC level in the input signal is given as

$$PRD(\%) = \frac{\sum_{n=1}^{N} \left(f(n) - \hat{f}(n) \right)^2}{\sum_{n=1}^{N} \left(f(n) - \bar{f} \right)^2} \times 100 \tag{8}$$

Here, $f(n)$ is the input signal, $\hat{f}(n)$ is the recovered signal, $\bar{f}$ is the mean of the signal, and N is the length of signal.

3.2 Compression Ratio (CR)

CR is used to measure the reduction in the dimensionality of the signal and given as:

$$CR = \frac{M}{N} \tag{9}$$

where the input signal is of the length N and M is the number of measurements taken from sensing matrix.

3.3 Root-Mean Square Error (RMSE)

RMSE is given as:

$$RMS = \sqrt{\frac{\sum_{n=1}^{N} \left(f(n) - \hat{f}(n) \right)^2}{N}} \tag{10}$$

where, $f(n)$ is the original signal and $\hat{f}(n)$ is the recovered output signal and N is the length of input signal.

3.4 Signal-to-Noise Ratio (SNR)

SNR is given as

$$SNR = 10 \times \log \left(\frac{\sum_{n=1}^{N} \left(f(n) - \bar{f} \right)^2}{\sum_{n=1}^{N} \left(f(n) - \hat{f}(n) \right)^2} \right) \tag{11}$$

where $f(n)$ is the original input signal, $\hat{f}(n)$ is the recovered output signal, $\bar{f}$ is the average of the signal, and N is the length of input signal.

3.5 Sparsity

When a given signal contains only few no. of nonzero (K) coefficients, it is called as sparse signal and given as

$$\text{Sparsity}(\%) = \frac{(N - K)}{N} \times 100 \tag{12}$$

where, N is the signal length, K is the number of nonzero coefficients of the signal and $(N\text{-}K)$ is the number of discarded coefficients of the signal.

4 Application of Compressed Sensing (CS) for ECG Signal Compression

An extensive literature survey have been performed on CS-based ECG compression papers. Table 1 shows the comparative summary of literature papers for CS-based ECG signal compression.

Pooyan et al. [2] tested wavelet transform on the ECG signal and SPIHT technique is used to encode the coefficients. SPIHT achieves CR = 21.4, PRD = 3. 1 with a very good reconstruction quality and outperforms all others compression algorithm. SPIHT has a low computational complexity and easy to implement. Polania et al. [17] proposed a 1-lead compression method. In this, the ECG signal's quasi periodic nature is exploited in between adjacent beats of samples. The author utilized the distributed compressed sensing to explore the common support between samples of adjacent beats. The drawback of the scheme is increase in the computational complexity at encoder. Experimentation is performed using the MIT-BIH Arrhythmia Database. The proposed CS-based scheme accomplishes a good CR for low PRDs and also out performs SPIHT. Polania et al. [18] incorporate two properties of signal structure; in the first property the wavelet scale dependencies are included into the recovery methods and second used the great common support

Table 1 Comparative summary of literature for CS-based ECG signal compression

Author	Sparsity basis, sensing matrix, reconstruction algorithm used	PRD (%)	CR	Strengths/Findings
Pooyan [3]	Set partitioning in hierarchical trees (SPIHT) algorithm	3.1	21.4	High efficiency, easy to implement, computationally simple
Polania [17]	Daubechies wavelets (db4), random gaussian matrix, SOMP	2.57	7.23	Achieves a good compression ratio, outperforms SPIHT as the PRD increases, offers a low complexity encoder
Polania [18]	Wavelet transform-based tree-structure model, bernoulli matrices, MMB-CoSaMP and MMB-IHT (Record no.100)	IHT = 3.65, CoSaMP = 3.86	6.4	Simple hardware design, less data size, and small computational need
Daniel [22]	Wavelet bases, random bernoulli matrix, BP	9	2.5	Simple encoder design
Ansari-Ram [23]	Biorothogonal4.4, nonuniform binary matrix, convex optimization	8.58	5	Increases the overall PRD
Akanks-ha Mishra [19–21]	29 different wavelet families like coiflets, daubichies, symlets, biorthogonal, reverse biorthogonal, random gaussian matrix and KLT sensing matrix, BP	0.01 0.01	2 2	rbio3.9 shows best sparsity. KLT sensing matrix superior than gaussian matrix
Anna Dixon [24, 25]	Random gaussian matrix, convex optimization, OMP, CoSaMP, ROLS, NIHT	–	–	CoSaMP and L1-norm convex gives best accuracy, CoSaMP preferred in noisy conditions, OMP is best for low computational complexity
Mamaghanian [33, 36]	Wavelet basis, random gaussian matrix, BP	<9	3.44	PRD = 0–9 % is "good or very good" ECG signal quality

of wavelet domain coefficients. The two model-based algorithms namely modified model-based MMB-CoSaMP and MMB–IHT are evaluated. For compression ratio CR = 4, the PRD of MMB–IHT is 3.65 and for MMB-CoSaMP is 3.86. For nearly all the ECG records, MMB-IHT shows superior execution than MMB-CoSaMP.

- *Selection of Best Sparsity Basis for CS ECG Compression*

One of the primary research areas for ECG compression is the choice of sparsity basis. Mishra et al. [19, 20, 21] evaluated a best wavelet basis for ECG Signal compression using Compressed Sensing approach by comparing several wavelet families like Haar, Daubechies, Reverse Biorthogonal, and biorthogonal etc. These families were evaluated using the performance metrics such as MSE, PSNR, PRD, and Correlation Coefficient (CoC). Here, L1 optimization is used as the signal reconstruction method. The result analysis is performed for five different compression ratios, like 2:1, 4:1, 6:1, 8:1, 10:1 and from each CR the best fit wavelet family was identified. From reverse biorthogonal wavelet family, rbio3.7 and rbio3.9 shows the best results. Finally, the best Daubechies wavelet (db) is selected for specific CR. For CR 2:1, db4 is chosen. Similarly, for CR 4:1, db8 is selected. For CR 6:1, db4 is most suitable Daubechies wavelet.

- *Different Sensing Matrices for ECG Signal Compression*

Polania et al. [17] used Random Gaussian Matrix with zero mean and 1/m variance achieves a good compression ratio. Polania et al. [18] and Chae et al. [22] tested Bernoulli matrices results in small data storage, less computational complexity, and simple encoder hardware design. Mishra et al. [19, 20, 21] compared the random Gaussian matrix and KLT sensing matrix performance for different compression ratios: for Random Gaussian matrix with CR = 2, PSNR = 57.57, PRD (%) = 0.01, MSE = 1.57, COC = 0.9994 where for KLT sensing matrix with CR = 2, PSNR = 59.92, PRD (%) = 0.01, MSE = 1.20, COC = 0.9996. This result shows that KLT sensing matrix shows better performance than random Gaussian matrix. Ansari-Ram and Hosseini-Khayat [23] proposed a nonuniform measurement matrix. This matrix acquires the QRS complex, i.e., region of interest and increases the total PRD value. This method has a weakness since it is also required to transmit sensing matrix to decoder end.

- *CS Reconstruction Algorithms for ECG Compression*

Dixon et al. [24, 25] evaluated comparative analysis on state-of-the-art CS recovery algorithms: BP, convex optimization, OMP, CoSaMP, ROLS and NIHT based on metrics like computational time, accuracy and noise tolerance. When accuracy is needed CoSaMP and L1 based convex are the natural choices. In noisy conditions CoSaMP outperforms L1-norm convex. OMP is preferable where computational complexity is important like real-time implementation with low power consumption.

- *Performance of CS ECG with Different Sparsity and Noisy Conditions*

Chae et al. [22] evaluated the CS ECG compression performance under the noisy ECG signal acquisition and with varied heartbeat rate because of body movements. From results, we can conclude that the CS with noise is quite difficult to minimize because of nonlinear nature of the recovered noise. The CS performance is compared to TH-DWT for ECG compression, where TH-DWT outperforms CS in the sense of CR. Care should be taken while applying CS for ECG compression as the CS is very susceptible to noise and sparseness of the signal. The TH-DWT method attains a PRD of 9 % at a CR = 5 whereas for the same PRD the CS attains a CR = 1.67. With noisy signals, the TH-DWT shows a flat SNR up to a CR = 2.5 after which have a slight fall in SNR, while the CS performance sharply decreased from a CR = 1.25.

- *Application of Dictionary Approach for ECG Compression*

Polania and Barner [26] proposed the multiscale dictionary learning approach for the recovery of ECG signals and evaluated the results with wavelet and single scale dictionary approach. Results show that these dictionary learning-based schemes provide better performance than the CS scheme using standard wavelet dictionaries. A multiscale dictionary in CS schemes improves the quality of the recovered ECG signal when compared to single scale methods. The proposed method utilizes the different wavelet subbands information at various scales to efficiently learn sparse and redundant dictionaries for representation of the ECG. Pant and Sridhar Krishnan [27] proposed the dictionary learning algorithms which produce a dictionary which can be used with L_p^{2d}–RLS method. This approach significantly improves signal recovery performance of L_p^{2d-}RLS method for ECG signals.

Fira et al. [28, 29] obtained the best results for the CPCS method using optimized projection matrix and patient-specific dictionary. The optimized dictionaries show the excellent results for all the records. The great extent of quality score achieved, for a 15:1 CR, 0.97 PRD and 15.46 QS is 50 % with CPCS technique with patient-specific heart beats (PRD = 0.51, QS = 29.13) without preprocessing. Singh and Dandapat [30] proposed distributed CS (DCS) for multichannel ECG signals with sparse learned dictionary, which are suitable for sparsity control of a signal. Pathology-specific and normal overcomplete dictionaries are used as the sparsifying basis and learnt using K-SVD algorithm. This improves the efficiency of the conventional CS in views of data size and reconstruction time.

- *Bayesian Learning Approach for ECG Compression*

Zhang et al. [31] proposed the Bayesian learning approach for the reconstruction of ECG signal which is sparser than existing compressed sensing solutions and it is also faster due to the improved sparsity. However, Bayesian approach has a drawback such as lack of theoretical foundation between the Bayesian approach, RIP, and incoherence. Some of the approaches fulfill the condition of RIP and incoherence, but in case of the full rank Fourier matrix, the BCS is failed. Zhang et al. [32] successfully applied the block sparse Bayesian learning (BSBL) structure to

compress as well as recover non-sparse FECG signal and improved the performance using the correlation structure of signals. Experiments are performed on the DaISy Dataset and the OSET Dataset. Same sensing matrix is used with every experiment for all the CS methods used to compress FECG recordings. Two categories CS algorithms are tested. First category of recovery methods do not utilize block structure of signals includes CoSaMP, BP, SL0, Elastic-Net, and EM-GM-AMP which are from the class of greedy algorithms. The Basis Pursuit algorithm is used to reconstruct adult ECG recordings. The second group of algorithms utilized the structure of signals which includes, Block Basis Pursuit, Block-OMP, StructOMP, BM-MAP-OMP, and CluSS-MCMC. Block Basis Pursuit and Block-OMP requires a priori information of the block division. The result of comparison shows satisfactory quality with BSBL-BO algorithm. The BSBL-BO is evaluated for various factors such as impact of, the block partition effects, effect of compression ratio, and the impact of number of nonzero column entries of the sensing matrix. The proposed framework can be employed to many other telemedicine applications, such as wireless electroencephalogram, and electromyography.

- *On Quality of the Recovered ECG in the Views of Clinical usage*

Mamaghanian et al. [33] evaluated the PRD values for NIHT, EIHT, and FLIHT using the wavelet tree model. Among all, EIHT shows the great degrees of performance for S-Sparse signals. For model-based reconstruction methods MB-NIHT accomplish 95 % and more successful recoveries for M = 160 number of measurements. The same is achieved for M = 224 with EIHT and M = 192 with MB-FLIHT. Hence, NIHT and FLIHT results in a improved signal recovery performance in view of the probability of signal reconstruction and the output recovered PRD. This research shows that PRD values from 0–9 % are considered as "good or very good" ECG signal quality for clinical diagnosis. Zigel et al. [34] suggested a novel distortion metric named weighted diagnostic distortion (WDD) for ECG signal compression. The result shows that the suggested WDD metric is most appropriate for evaluating ECG recovered signals compared to the PRD metric. Drawback of WDD is that it is expensive to calculate compared to inexpensive measure of PRD.

- *Real-Time CS Hardware Implementation for ECG Signal Compression*

In the recent years significant research focus and efforts are made on the design, development and implementation of real-time CS hardware for different applications. Duarte et al. [35] proposed the one pixel imaging using CS. Body area network (BAN) is one of the recent application which is explored by many publications. Mamaghanian et al. [36] evaluated the performance of CS for wireless BAN on shimmer embedded platform which outperform DWT based lossy compression technique. Mishali et al. [37] designed "analog-domain CS system—a modulated wideband converter (MWC)". Chen et al. [38, 39] presented digital based CS for ECG and EEG signals. Dixon et al. [25] evaluated the performance of bio-medical signal sensors for BAN application on real time hardware.

5   Conclusion

In this review paper, we have presented a complete survey of the CS area for 1-dimensional biomedical application focused on CS-based ECG signal compression. We have investigated the basic of CS technique and discussed theoretical and mathematical basis of the important concepts. We have presented the reviews on some of important areas of CS-based ECG compression like choice of most excellent wavelet basis function for maximum sparsity of ECG signal, different sensing matrices for ECG signal compression, evaluation of CS reconstruction algorithms for ECG signal recovery with good accuracy and less reconstruction time, performance of CS ECG signal in different sparseness and noisy conditions, application of dictionary approach for ECG compression, Bayesian learning approach for ECG signal compression or recovery and real-time CS hardware implementation for ECG signal compression. Research on CS has demonstrated that CS is suitable alternative compared to the state of the art ECG compression techniques like SPIHT. From the review summary we can conclude that biorthogonal wavelet family rbio3.7 and rbio3.9 gives best sparsity, Bernoulli's matrices results in simple encoder design, OMP is the best choice for real time implementation. Dictionary learning approach will improve the CS reconstruction performance, while recently emerged Bayesian learning approach will even outperform CS-based approaches. Low power consumption and reconstruction quality of signal are the major challenges faced by real-time CS hardware implementation.

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