Chapter 2

Compression of ECG Signals for Tele-monitoring Applications: A Critical Review

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Abstract

Tele-monitoring and tele-healthcare systems have long been used primarily for monitoring elderly people, patients with mobility issues, and also to reduce the number of hospital visits for routine health-checkups. However, it could be undoubtedly said, that the tele-monitoring and tele-healthcare systems would be the prime choice of both the doctors and patients in the post COVID-19 era, in order to reduce the potential spread of the virus. The field of research of the compression of electrocardiogram (ECG) signals has been well studied over the last four decades, approximately. Recent trend in this area of research indicates that the researchers around the globe are getting more interested in developing not only efficient ECG compression techniques, but also such techniques which could also be utilized in tele-monitoring and tele-healthcare applications. In this chapter, a literature survey is presented on the ECG signal compression techniques pertaining to the tele-monitoring and tele-healthcare systems, which have been proposed in the literature in the last ten years. A number of key factors, such as the compression performance, clinical acceptability of the reconstructed

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signals, likelihood of implementation of an ECG compression technique in tele-monitoring and tele-healthcare systems, are critically analyzed in this survey. Finally, some open problems in this area of research are suggested.

Keywords: ECG compression; Tele-monitoring; Tele-healthcare.

1. Introduction

Recent advancements in the field of miniaturized device fabrication technologies have enabled acquisition and monitoring of electrocardiogram (ECG) signals in portable hand-held devices. According to World Health Organization's (WHO) estimation 23.6 million individuals will die from cardiovascular diseases by the year 2030 [1,2]. ECG is considered as the prime human physiological signal [3], and is recorded by means of electrodes from a number of standardized locations on the torso. Presence of cardiac anomaly is often diagnosed from the ECG signal. However, ECG signals are highly subjective and therefore, symptoms of cardiac disorders may appear randomly. Therefore, monitoring of ECG signals has to be carried out for long periods. As a result, the amount of data to be stored becomes enormous. Here the ECG compression techniques come into play. The benefit of having an efficient ECG compression technique is two folds: first, it helps reducing the size of the acquired ECG signals, and second, it improves the transmission efficiency of the communication-link in real-time tele-monitoring applications. Maintaining the clinical quality of the ECG signal upon reconstruction is a prime requirement of an ECG compression technique and also, the higher the compression performance the better.

Based on the capability of preservation of clinical information, the ECG compression techniques could be broadly classified into two categories: lossless [4-7] and lossy [8,9]. The data-reduction performance of a lossless ECG compression technique usually happens to be less compared to that of a lossy one, but, it does not lose any clinical information. On the other hand, the compression performance of a lossy algorithm is high compared to that of a lossless one. However, a lossy compression technique might lose clinically significant information, which is not acceptable. Based on the methodology, the ECG compression algorithms could be broadly categorized into four major classes: direct [10], transformation-based [11,12], statistical redundancy-based [13,14] and prediction-based [15,16,7]. Compression of ECG signal is achieved by exploiting either the inter-sample or inter-beat (one complete ECG cycle is called a 'beat') correlation. The direct ECG compression techniques exploit the inter-sample correlation, and it is often seen that, the compression performance of a direct ECG compression technique improves with increasing the sampling rate of the ECG signal. Direct compression schemes are easy to implement on real-time systems and also they require less computational resources. On the other hand, the transformation-based techniques exploit the inter-beat correlation of the ECG signal, and utilize their energy compaction property to achieve a high compression performance. The transformation-based ECG compression techniques convert the time-domain ECG signal into some other domain, then discard the comparatively less significant, i.e., the redundant coefficients, and finally, encodes the rest of the coefficients. The prediction-based ECG compression techniques are mainly based on linear and long-term prediction algorithms. The ECG compression algorithms can also be classified in to another two categories: one-dimensional (1D) ECG compression [2,4,5,8-12] and two-dimensional (2D) ECG compression techniques [13,14,17-19], based on structure of the input-ECG-signal fed to the compression model. An ECG compression technique is considered to be 1D, when it takes the input ECG signal as an $N\times1$ (or $1\times N$) vector, where N is the total number of samples of the ECG signal. On the other hand, if the input to an ECG compressor is a matrix of dimension $N\times M$ (or $M\times N$), where M is either the number of ECG-beats or the number of ECG-channels, the technique is denoted as a 2D ECG compression technique. Along with the inter-sample and inter-beat correlation, a 2D ECG compression technique also exploits the intra-beat or intra-channel correlations.

After compression, the compressed ECG data is to be sent to the remote hospitals or clinicians for the purpose of tele-monitoring and tele-healthcare applications. Rapid advancements in the field of telecommunication; in particular, wireless and mobile communications, has opened an array of opportunities to the healthcare services [20]. A variety of wireless communication protocols such as code-division multiple access (CDMA) network [21], Global system for mobile communications (GSM) [22, 23], wireless mess network (WMN) [24], satellite communication [25], short message service (SMS) system [2, 26-28], industrial, scientific and medical (ISM) band [29], bi-phase modulation [30], Bluetooth connection [31], wide-area wireless network [32] and Wi-Fi connection [33] have been used for the transmission of the ECG signals to the remote site to expedite the tele-healthcare or tele-cardiology systems.

After receiving the compressed ECG signal at the remote site, the signal is be reconstructed as accurate as possible for the purpose of the clinicians visual inspection. The clinical acceptability of a reconstructed ECG signal could only be certified by the medical practitioners or doctors. A number of numerical metrics are also there to quantify the quality of the reconstructed ECG signals. The ECG quality assessment techniques could be categorized into two types: (1) objective assessment [34] and (2) subjective assessment techniques. The metrics, which are frequently used for the objective assessment of an ECG signals are: percent root mean square difference (PRD), normalized percent root mean square difference (PRDN), root mean square error (RMSE), cross correlation, maximum amplitude error (MAE), and quality score (QS). On the other hand the technique used for the subjective assessment is the mean opinion score (MOS) tests [35]. The schematic of an ECG-based tele-cardiology system is shown in **Figure 1**.

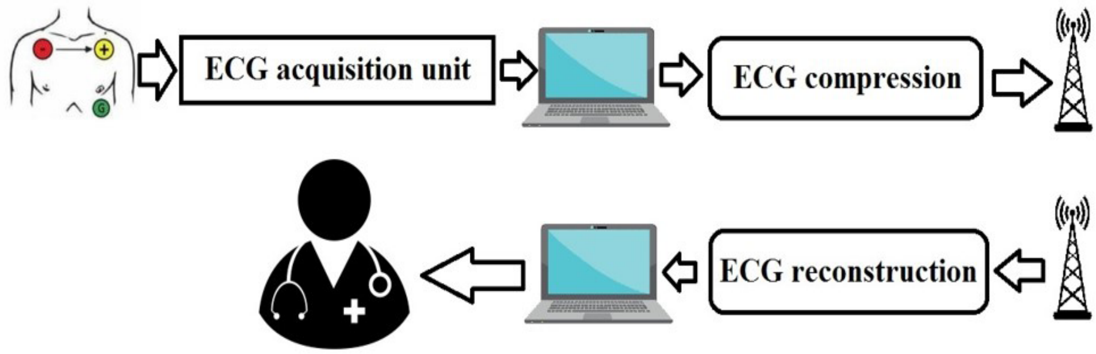

Figure 1: Schematic of an ECG-based tele-cardiology system.

This chapter is organized as follows. Section II describes the strategies that have been followed to search the relevant literature. The ECG compression techniques, which have been proposed in the literature pivoting the tele-cardiology applications, are surveyed in Section III, and the metrics, which are used to quantify the quality of the reconstructed ECG signals are analyzed in Section IV. The performance of a number of ECG compression techniques are analyzed in Section V. Finally, some open problems in this area of research are suggested in Section VI.

2. Strategy of literature search

A literature search is performed on the PubMed database of the US National Library of Medicine and Google Scholar in order to find the published articles in the area of ECG compression pivoting tele-cardiology applications. The keywords, which are used in the search operation are: 'ECG compression', 'tele-cardiology', 'tele-healthcare', 'tele-monitoring', and 'remote ECG monitoring'. Only those articles (journal and conference publications) that are written in English, and are published in between January 2010 to August 2020 are considered in this survey. In total, 150 published articles are reviewed, and after a rigorous and careful selection, 15 papers, which are based on compression and tele-healthcare applications of ECG signals are selected for this review. Also, those published literatures, which have dealt only with ECG compression, and have the potential to be used in tele-cardiology applications are considered, too.

3. ECG compression for tele-cardiology applications

A few ASCII (American Standard Code for Information Interchange) character encoding-based lossless and lossy ECG compression algorithms have been proposed in the literate for tele-cardiology applications [2,26]. In [2], first, the ECG signal is segmented into several blocks of durations 0.016 seconds each. Then, the standard deviation of each block is calculated. If the standard deviation of any block of data is found to be higher than that of an empirically determined threshold, then that particular block of ECG data is compressed using a lossless technique, otherwise it is compressed using a lossy technique. In [2], it has been hypothesized that those blocks of data having a high standard deviation correspond to the QRS-complex regions. Since, the QRS-complex regions of an ECG signal hold the most important clinical information, these regions are compressed using a lossless technique, and the non-QRS-complex regions are compressed using a lossy compression technique. Both the lossless and lossy compression techniques designed in such a way, that, the compressed data contains only ASCII characters. These ASCII characters are then transmitted to the remote site using SMS system. A GSM modem (model i-300) is connected through the computer serial port, and is used to send the SMSs. At the receiving site, all the SMSs are concatenated, and the ECG signal is reconstructed. A similar technique is used in [26] for the compression and remote transmission of ECG signals. The main difference between the techniques, which are proposed in [2] and [26], respectively, lies in the method of detection of the QRS-complex regions. In [2], the QRS-complex regions are identified using a standard deviation-based technique, whereas a slope-thresholding-based approach is used in [26] to detect the QRS-complex regions. Both the techniques, which are proposed in [2] and [26] are example of direct ECG compression technique. Another ECG compression technique employing ASCII character encoding and SMS-based tele-cardiology system is proposed by Mitra et al. in [28].

Mukhopadhyay et al. have proposed a singular value decomposition (SVD) and ASCII character encoding-based multi-channel ECG compression technique in [13]. In [13], ECG signals of eight channels, namely lead I, II and V1 to V6, are taken and are arranged in the form of a matrix of dimension $N \times M$, where N is the number of samples in each ECG channel and M is the number of ECG channels. The matrix is then decomposed using SVD technique. SVD technique decomposes a matrix into two orthonormal and one diagonal matrices. Elements of the diagonal matrix are in descending order of magnitude and are called the singular values. If the correlation among the data present in the matrix is high, then most of the energy is expected to be concentrated over the first few singular values. The matrix factorization technique can be written as below.

$$A = USV^T \tag{1}$$

where the matrices U, S, V and A are, respectively, of the orders $N \times M$, $N \times N$, $N \times M$, and $M \times M$, $U^T U = I$, $V^T V = I$, and U and V are, respectively, the left and right singular matrices. The matrix S is a diagonal matrix, whose diagonal elements are the square roots of the eigen values of U arranged in the descending order followed by the square roots of the eigen values of V also arranged in the descending order. Next, the relatively small singular values, which contain less-significant clinical information, are discarded and all the three matrices U, S and V are truncated accordingly. The truncated elements of these three matrices are then compressed using an ASCII character encoding-based technique. An ad hoc website is developed in [13] for the purpose of storage of the compressed ECG data and tele-healthcare applications. The compressed data is uploaded to the website and clinician (s) are assigned for that particular ECG signal. Auto-generated emails are sent to the assigned clinician (s) as soon as the data is uploaded to the website, requesting them to diagnosis the ECG signal and give their feedbacks. Clinicians' feedbacks are then communicated to the patient so as to enable the patient taking precautionary measures. The ECG compression technique, which is proposed in [13] is an example of 2D ECG compression technique. This technique utilizes the inter-channel and inter-samples correlation of the ECG signal to reduce the size of the ECG data. A similar type of ECG compression algorithm employing SVD and ASCII character encoding technique is proposed in [36]. In [36], the QRS-complexes are detected from the 1D ECG signal, and the extracted QRS-complexes are arranged in the form of a $N \times M$ matrix, where M is the number of QRS-complexes and N is the number of samples in each QRS-complex. Then the matrix is decomposed using SVD and the truncated elements of the three matrices are compressed using the ASCII character encoding-based technique. The technique, which is proposed in [36] has not been used for a tele-monitoring application. However, the compressed data in [36] contains ASCII characters as in [2, 26] and [13], and hence, an SMS-based technique can be implemented alone with the compression module to make the technique useful in tele-cardiology applications. **Figures 2** and **3** show the ECG compression and reconstruction performances of the techniques, which are proposed in [13] and [36], respectively.

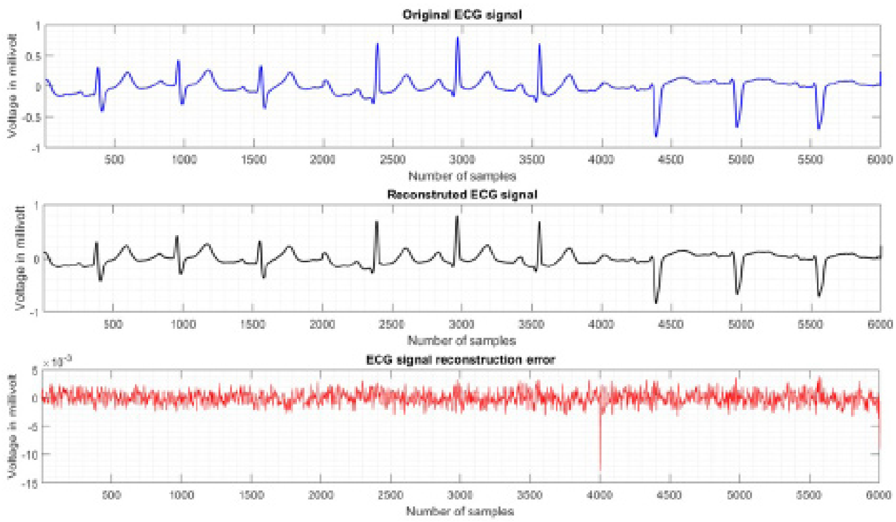

Figure 2: ECG compression and reconstruction performances of technique [13].

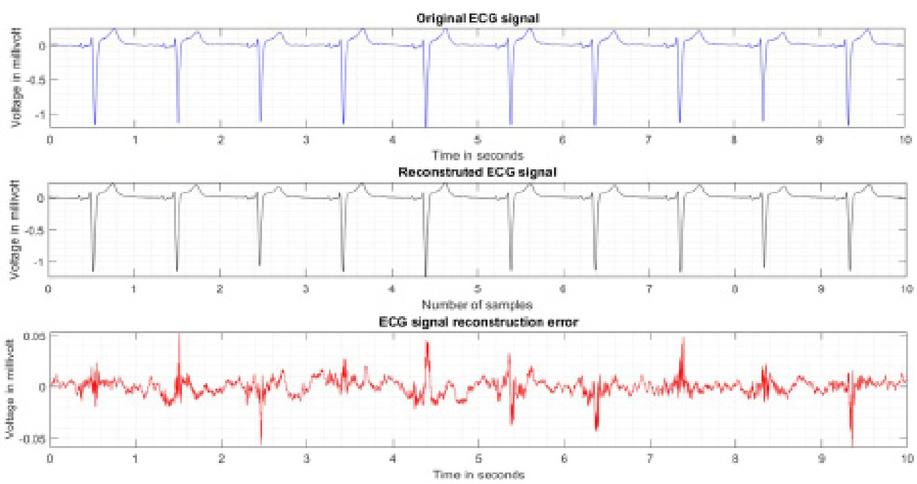

Figure 3: ECG compression and reconstruction performances of technique [36].

In [21], Kim et al. have presented a survey on wavelet transformation (WT)-based ECG compression algorithms in the context of tele-healthcare applications. The authors of [21] have implemented a few other WT-based ECG compression algorithms [37-39], and tried to find the most suitable technique for a tele-healthcare application over a code-division multiple access (CDMA) network. Compressed data, i.e., the compressed wavelet coefficients, obtained using all these three techniques are separately transmitted to a remote site using CDMA network under two different settings: simulation and real-time. Transmission of wavelet coefficients in simulation setting are tested with both noise-free and with random noises environments. The real-time transmission of wavelet coefficients over a CDMA network is conducted at different locations of Seoul, South Korea. Finally, it was concluded in [21], that the: ECG compression technique, which is proposed in [38] is a suitable to use in tele-monitoring applications over a CDMA network when the loss of data over the communication channel is low, and the technique [39] is suitable when the loss of data over the communication channel is relatively high.

An optimal zonal wavelet-based ECG data compression (OZWC) method for tele-healthcare systems has been proposed by Istepanian et al. in [22]. In [22], the ECG signal is decomposed into a number of frequency-band using wavelet transformation. Then, the wavelet coefficients are quantized using a uniform quantizer with 16-bit of resolution. The quantized coefficients are then coded using an entropy encoder. Next, the coded bit-stream is transmitted to the remote site using a GSM channel (standard 5.05) with a data rate of 9.6 kbit/s [23]. The ECG data is received and reconstructed at the remote site using an approach, which is reverse to the compression.

A satellite communication-based tele-monitoring system is proposed in [25]. ECG signals are recorded from the subjects at an altitude of 36,000 Km of Mount Logan in Yukon, Canada. Then the acquired signal is compressed and transmitted using a Mobile Satellite (MSAT-1) to the University of Ottawa Heart Institute with a data transmission rate of 2400bits/second. The distance covered between the transmitter and the receiver sides is more than 4,000 Km, and the coverage area of the satellite includes Canada, the US, Mexico and parts of the Caribbean Central America.

Alesanco et al. have proposed a wavelet transformation-based ECG compression algorithm, and it’s real time remote transmission over the transmission control protocol/internet protocol (TCP/IP) for tele-cardiology applications in [32]. In [32], the ECG signal is decomposed into a number of frequency-bands using wavelet transform, and the coefficients are compressed using set partitioning in hierarchical trees (SPIHT) technique. The SPIHT technique has received a widespread recognition for its notable success in image coding. A detail explanation of the SPIHT technique can be found in [40]. A Markov model has been used to simulate the wireless channel through which, the compressed data it transmitted to the remote site. In the developed data transmission model in [32], a provision has also been kept in order to re-transmit the compressed ECG data in the case of an erroneous data transmission.

Gupta has presented a principal component (PCA) analysis, run length encoding and Huffman coding-based ECG compression technique in [19]. In [19], first, the ECG signal is denoised using a wavelet transformation-based technique [13]. Then, the QRS-complexes are detected from the ECG signal. Detected QRS-complexes are then arranged in the form of a matrix. The matrix is then decomposed using the PCA technique. Principal component analysis (PCA) [41] is a statistical signal processing tool, which is often used to factorize matrices in order to extract the hidden information from multivariate data. In PCA technique, an orthogonal transformation is used in order to map the original correlated data to a set of mutually uncorrelated vectors, named the principal components (PCs). The PCs are obtained in decreasing order of their variances, and hence in many cases only few of these PCs are found to be sufficient to represent the variability of the data. Therefore, the less-contributing PCs could be truncated to achieve a reduction in the data size without jeopardizing the information present in the original dataset. The orthogonal transformation can be written as below.

$$P = AE^T \quad (2)$$

where P is a matrix of order NXM containing the principal components of the matrix A, and E is a matrix of order MXM containing the eigenvectors of the matrix A. Next, the truncated elements of both the P and E matrices are compressed using run length encoding and Huffman coding techniques. This technique of ECG compression falls in the category of both direct and statistical redundancy-based ECG compression technique. The performance of this technique has not been tested for a remote tele-cardiology system. However, the compressed ECG data in [19] contains a string of binary data, and hence, an SMS or GSM or CDMA-based data transmission technique can be used alone with the compression module to make the technique useful in tele-cardiology applications.

In [17], Pandey et al. have proposed a 2D ECG compression algorithm using discrete cosine transform (DCT) and JPEG2000 encoding-based techniques. This technique of ECG compression falls under the category of transformation-based technique. In [17], first, the DCT coefficients of the ECG signal are computed. DCT coefficients are then quantized using a differential pulse-code modulation (DPCM)-based technique. Finally, the quantized bits are further compressed using the JPEG2000 technique. The JPEG2000 is a popular discrete wavelet transform-based compression technique [42], which is primarily developed for the compression of images. Here also, as in [19], the performance of this technique has not been tested for a remote tele-cardiology system but, the compressed ECG data in [17] contains only binary data. Therefore, an SMS or GSM or CDMA-based data transmission technique can be used alone with the compression module to make the technique useful in tele-cardiology applications.

A transformation-based 2D ECG compression technique is proposed by Chagnon et al. in [18]. In [18], first, the QRS-complexes are detected from the ECG signal using a technique, which is developed in [43]. Next, the detected QRS-complex are arranged in the form of a matrix. Then, a 1D discrete wavelet transform is applied along the rows, and a 1D discrete cosine transform is applied alone the column of the matrix. Only a few significant transformed-coefficients are retained in order to make sure that the reconstructed signal would not lose much clinical information upon reconstruction. Then, those coefficients are encoded, and finally the encoded coefficients are further compressed using Huffman coding technique. Here also, as in [19] and [17], the performance of this technique has not been tested for a remote tele-cardiology system but, the compressed ECG data in [18] contains only binary data. Therefore, an SMS or GSM or CDMA-based data transmission technique can be used alone with the compression module to make the technique useful in tele-cardiology applications.

An Atmel 89C52 microcontroller-based acquisition of ECG signals, bi-phase modulation-based encoding and wireless transmission over industrial, scientific and medical (ISM) band have been proposed by Gupta et al. in [29] and [30]. The acquired ECG signals are segmented into packets containing 256bits each. Then, each packet of data is modulated using a Quadrature Phase Shift Keying (QPSK) technique. Then, the modulated data packets are transmitted to the receiver site using a cord-less telephone operating at the 2.4 GHz ISM band. At the receiving site, the ECG signal is decoded using a technique, which is reverse to encoding.

The downside of the traditional ECG acquisition systems is that, they cannot be used for long term recording and also they are bulk in size. In the case of long term ECG recording a Holter ECG recorder is often used. However, the weight of a Holter recorder is also no less, and the patient needs to carry the device for 24 to 48 hours, depending on the clinical requirement. Moreover a number of ECG-sensors are connected to the torso during a Holter recording, which often makes the patient feel uncomfortable. However, the recent trend of research and development has shown a booming interest in developing comfortable, wearable and long term ECG acquisition and monitoring systems [31,44]. In [31], Ozkan et al. have developed a wearable textile ECG electrodes, that can acquire ECG signal for over 14 days at once. Besides acquiring the ECG signal, the embedded circuitry also transmit the data in real time to the user’s smart phone using Bluetooth connection for visual inspection. The developed system also calculate the heart rate in real-time. The acquired ECG data is then uploaded to a remote internet of thing (IoT) server for analysis at a later time.

4. Quality analysis of reconstructed ECG signals

After compression and remote transmission, it is necessary to examine the compression performance as well as the clinical quality of the ECG signal upon reconstruction. Compression ratio (CR) is a figure-of-merit of a compression technique. CR is expressed as the ratio of the original and the compressed data file-size.

$$CR = \frac{Size\ of\ the\ original\ ECG\ data}{Size\ of\ the\ compressed\ ECG\ data} \tag{3}$$

The clinical acceptability of an ECG signal could only be enumerated by trained medical practitioners or doctors. A few reliable numerical metrics are also there to assess the commonality between the original and the reconstructed ECG signals. The fidelity assessment techniques of the ECG signal could be categorized into two types: objective assessment and subjective assessment techniques. The objective assessment techniques are two types in nature: non-diagnostic and diagnostic distortion measures. The goal of an ECG compression algorithm is to maximize the CR value keeping the reconstruction error as less as possible.

4.1. Non-diagnostic distortion measures of ECG signals

Popular non-diagnostic ECG distortion measures, which are widely used for the objective assessment of reconstructed ECG signals include (i) percent root mean square difference (PRD), (ii) normalized percent root mean square difference (PRDN), (iii) cross correlation (CC), (iv) root mean square error (RMSE), (v) maximum amplitude error (MAE) and (v) quality score (QS).

The percent root mean square difference (PRD) is expressed as

$$PRD(\%) = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \hat{x}_i)^2}{\sum_{i=1}^{N} x_i^2}} \times 100 \tag{4}$$

where x_i is the i^{th} sample of the original ECG signal, $\hat{x}_i$ is the i^{th} sample of the reconstructed ECG signal, and N is the total number of samples.

As per the globally accepted standard [35], the quality of a reconstructed ECG signal is considered to be 'very good' if the PRD value lies in the range 0 - 2%. The quality of the ECG signal is considered to be 'good', if the PRD value lies between 2% - 9%, a PRD value in the range of 9% - 19% is considered as 'not good', and a PRD value beyond 19% is considered as a 'bad' quality of reconstruction.

However, in the presence of low frequency noises such as a baseline wander or DC shift in the baseline of the ECG signal, Equation 4 often generates a low vale of PRD, which is misguiding. The reason behind this, is that the presence of a baseline wander or DC shift makes the denominator part of Equation 4 high, and results a low PRD value. Therefore, the use of a high-pass filter in order to remove the low frequency noises beforehand is preferred. The above mentioned problem, which is associated with the equation of PRD could be minimized using Equation 5, if the low frequency noise present in the ECG signal is DC in nature.

$$PRDN(\%) = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \hat{x}_i)^2}{\sum_{i=1}^{N}(x_i - m_x)^2}} \times 100 \qquad (5)$$

where PRDN is termed as normalized PRD and m_x is the mean of the original ECG signal. The root mean square error (RMSE) is another non-diagnostic ECG distortion measure, and is expressed as

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \hat{x}_i)^2}{N}} \qquad (6)$$

The cross correlation (CC) is the metric of measure of similarity between two signals, and it is expressed as

$$CC = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - m_x)(\hat{x}_i - \widehat{m}_x)}{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - m_x)^2}\ \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{x}_i - \widehat{m}_x)^2}} \qquad (7)$$

where $\widehat{m}_x$ is the mean of the reconstructed ECG signal. The value of CC varies between 0 and 1. The value of CC becomes 1, if the reconstructed ECG signal happens to be an exact replica of the original one. Only a strict lossless ECG compression technique could provide a CC value of 1. Maximum amplitude error (MAE) is another non-diagnostic distortion measure of ECG and is expressed as

$$MAE = max(|x - \hat{x}|) \qquad (8)$$

MAE represents the maximum amplitude of error between the original and the reconstructed ECG signals.

Quality score (QS) is another metric, which is expressed as the ratio of the compression performance and PRD;

$$QS = \frac{CR}{PRD} \qquad (9)$$

The value of QS approaches to infinity for a strict lossless compression.

The smaller the values of PRD, PRDN, RMSE and MAE, and the higher the values of CR, CC and QS, the better the ECG compression technique.

4.2 Diagnostic distortion measures of ECG signals

There are a few metrics, which enumerate the amount of distortion present in the reconstructed ECG signals through the analysis of diagnostic information only, instead of calculating the sample-to-sample differences as described in Section 4.1. Example of such objective diagnostic-distortion measurement techniques are: (i) wavelet energy-based diagnostic distortion (WEDD) [34], [45] and (ii) weighted diagnostic distortion (WDD) [35]. The WEDD between the original and reconstructed ECG signal is calculated following the steps given below.

STEP 1: The mean values of the original and reconstructed ECG signals are calculated and subtracted from the respective signals as

$$x \leftarrow x - m_x \tag{10}$$

$$\hat{x} \leftarrow \hat{x} - \hat{m}_x \tag{11}$$

STEP 2: Decompose both x and $\hat{x}$ into L+1 bands using discrete wavelet transform selecting a suitable mother wavelet function.

STEP 3: Calculate the dynamic weights of each of the frequency bands of x.

$$W_B(l) = \frac{\sum_{j=1}^{N}\left(B_l(j)\right)^2}{\sum_{i=1}^{L+1}\sum_{j=1}^{N}\left(B_i(j)\right)^2} \quad l = 1, 2, \ldots, L+1 \tag{12}$$

where $W_B(l)$ is the dynamic weight of the l^{th} wavelet-band, and $B_l(j)$ is the j^{th} wavelet-coefficient of the l^{th} frequency band of x.

STEP 4: Calculate the error in the wavelet-coefficients of each band of x and $\hat{x}$

$$W_{PRD}^{l} = \sqrt{\frac{\sum_{j=1}^{N}[(B_l(j) - \hat{B}_l(j)]^2}{\sum_{j=1}^{N}(B_l(j))^2}} \quad l = 1, 2, \ldots, L+1 \tag{13}$$

where $\hat{B}_l(j)$ is the jth wavelet-coefficient of the l^{th} band of $\hat{x}$ as

STEP 5: Calculate WEDD as follows

$$WEDD\,(\%) = \left(\sum_{l=1}^{L+1} W_{PRD}^{l} \times W_B(l)\right) \times 100 \tag{14}$$

As per the WEDD standard [45] the quality of a reconstructed ECG signal could be considered as: ‘Excellent’, if the value of WEDD lies between 0-4.517%, ‘Very good’, if the WEDD varies between 4.517%-6.914%, ‘Good’, if the WEDD ranges between 6.914%-11.125% and ‘Not bad’, if the WEDD ranges between 11.125-13.56%. A WEDD value above 13.56% is considered as a ‘Bad’ quality of ECG reconstruction.

In calculating the weighted diagnostic distortion (WDD), first, a number of features are such as the durations and amplitudes of the QRS-complexes, T-waves, P-waves, are extracted from both the original and reconstructed ECG signals. Then the difference between each of the feature values are calculated. These difference values are then multiplied with a set of predefined weight values, and finally, the average of the product values is considered as WDD [35]. The lower the values of WEDD and WDD, the better the quality of the reconstructed ECG signal.

4.3 Subjective assessment of ECG signals

A subjective assessment, perhaps, could provide the best insight into the quality of a reconstructed ECG signal. Subjective assessment is done by the clinicians, doctors or domain-experts, and are of two types in nature (i) blind and (ii) semi-blind mean opinion score tests (MOS) [35]. The steps that are performed in doing a blind MOS test are given below.

STEP 1: Prepare a list of queries concerning the diagnostic features of ECG signals such as the QRS-duration, QRS-height, and polarity of the T-wave.

STEP 2: Provide the original ECG signal along with the list of queries to the doctor, and ask the doctor to answer the queries.

***STEP* 3:** Provide the reconstructed ECG signal along with the same queries to the doctor at a later point of time, and ask the doctor to answer the queries.

STEP 4: Calculate the numerical difference between these features values given by the same doctor.

***STEP 5*:** Follow steps 1 to 5 with other doctors or domain-experts, and calculate the MOS of the ECG signal by averaging of the difference between these features values.

On the other hand, in the case of performing a semi-blind MOS test, both the original and reconstructed ECG signals are provided to the doctors or domain-experts along with a list of queries as done in the case of a blind MOS test. They were asked to compare these features and to give a score in accordance with their similarities. The quality ratings are 5 (identical), 4 (very good), 3 (good), 2 (not bad) and 1 (completely different) [34, 35]. MOS of the ECG signal is then calculated using

$$MOS = \frac{1}{E \times F} \sum_{e=1}^{E} \sum_{f=1}^{F} Q(e, f) \tag{15}$$

where E is the total number of evaluators, F is the number of features, and Q is the quality rating of the f^{th} feature given by the e^{th} evaluator.

The smaller the values of MOS, the better the quality of the reconstructed ECG signal. As per the gold standard subjective measure a MOS value: (i) between 0 to 15% represents a ‘very good’ quality of ECG reconstruction, (ii) between 15% to 35% represents a ‘good’ quality of ECG reconstruction, (iii) between 35% to 50% represents a ‘not good’ quality of ECG reconstruction, and (iv) beyond 50% represents a ‘bad’ quality of reconstruction.

5. Performance analysis

A number of efficient ECG compression techniques, which have been developed over the last 10 years in order to expedite the tele-healthcare or tele-cardiology systems, are discussed in Section 3. It is also important to evaluate the performance of these ECG compression techniques. Section 4 discusses about a few numerical metrics and methods, which are widely used in order to enumerate the performance of an ECG compression technique. A number of online databases are there from where the ECG data of both normal and abnormal classes can be downloaded freely, and could be used as the performance evaluation testbed of an ECG compression algorithm. MIT-BIH arrhythmia database (MITDB) and PTB diagnostic ECG database (PTBDB) [46] are the two most popular ECG databases to the researchers for benchmarking an ECG compression algorithm. The MITDB contains 48 ECG records of duration 30 minutes each. All the 48 record of MITBD are acquired at a sampling rate of 360 Hz with 11-bits of resolution. The PTBDB contains 549 records of duration 1 minute each. In PTBDB the ECG signals are recorded at a sampling rate of 1 KHz with 16-bits of resolution. Now, a comparative analysis of the various ECG compression techniques discussed in Section 3 is carried out using the numerical values of the different metrics given in **Table 1**.

Table I: Comparative analysis of different ECG compression techniques.

Technique	Database	CR	PRD (%)	PRDN (%)	WEDD (%)	PUDT[1]	SDT[2]
[2]	PTBDB	22.51	7.34	17.26	-	SMS	Medium
[26]	PTBDB	22.47	7.58	13.28	-	SMS	Medium
[17]	PTBDB	17.04	4.58	-	-	-	-
[28]	MITBIH	39.12	4.54	7.42	-	SMS	Medium
[36]	MITBIH	63.93	8.09	8.09	6.41	-	-
[37]	MITBIH	9.78	0.86	-	-	CDMA	Fast
[38]	MITBIH	8.00	2.6	-	-	CDMA	Fast
[22]	MITBIH	18.1	-	-	-	GSM	Fast
[25]	Personal database	-	-	-	-	Satellite	Very fast
[19]	MITBIH	50.74 (max)	16.22	16.22	-	-	-
		9.48 (min)	4.13	4.13	-	-	-
[17]	MITBIH	39.48	2.02	-	-	-	-
[18]	MITBIH	39.00	0.60	-	-	-	-

[1]Protocol used for data transmission. [2]speed of data transmission.

It can be seen from Table I that the ASCII character encoding-based ECG compression algorithms, which are proposed in [2] and [26] provide a CR of about 22.51 and 22.47, respectively, keeping the PRD values less than 9%. A PRD value less than 9% suggests a ‘good’ quality of ECG reconstruction. Both these ECG compression techniques are used in tele-cardiology applications using SMS protocol. However, the speed of data transmission using SMS is less compared to that of a CDMA or GSM protocol. The performance of the ECG compression technique, which is proposed in [28] is tested on MITDB. The technique [28] attains an attractive compression performance (CR=39.12) keeping the PRD value even less than 5%. This technique of ECG compression is also used in tele-cardiology applications using SMS protocol. The SVD and ASCII character encoding-based ECG compression technique, which is proposed by Mukhopadhyay et al. in [36] achieves a CR value (CR=63.93) which is even better than that of in [28]. However, the ECG signal reconstruction error in [36] (PRD=8.09%) is almost 1.78 times higher than that of [28]. The performance of the technique [36] is not tested for a tele-cardiology application. However, since the compressed data contains only ASCII characters in [36], this ECG compression technique could be connected to an SMS-based tele-cardiology application as done in [2] and [26]. The wavelet transform-based ECG compression algorithms, which are proposed in [37] and [38], respectively, achieve an excellent PRD values, which suggests that the quality of reconstructed ECG signals using these two techniques falls under the category of 'very good'. However, the compression performance of these two algorithms are poor compared to others in Table I. CDMA protocol has been used with both these compression techniques to check the feasibility in tele-cardiology applications. The wavelet transform-based ECG compression technique, which is proposed in [22] offers a moderate-to-high compression performance (CR=18.1), and the technique is tested with a GSM protocol for tele-cardiology applications. The data transmission speed of both the CDMA and GSM protocols are higher than that of an SMS protocol. Satellite communication protocol is used [25] in order to set up a tele-healthcare network. In [25], the protocol is validated on ECG signals, which are collected from a group of researchers who were participated in the same research work. It has been shown in [25] that using a satellite communication protocol a larger area could be covered, and data could be transferred faster compared to that of a CDMA or GSM protocol. However, the cost of data transmission over a satellite communication network is much higher. The ECG compression techniques, which are proposed in [17,18] and [19] are not tested for tele-cardiology applications. However, considering their high compression performance and low signal reconstruction error, it could be said that these three techniques could also be used in tele-cardiology or tele-healthcare applications.

6. Some open problems in this area of research

Electrocardiogram (ECG) is considered as the prime human physiological signal. The presence of cardiac anomaly is generally reflected in the ECG waveform [13]. In clinical settings, ECG signals are recorded from a number of standardized locations on the surface of human body using 12 channels. Such a multiple-channel ECG signal acquisition gives the doctors/clinicians a complete three-dimensional view of the heart, which helps them in making an accurate diagnosis. However, most of the tele-cardiology systems, which are reported in the literature over the last ten years are based on single channel ECG signal. Therefore, the area of research of developing fast and reliable tele-cardiology system with multiple ECG signals is a long over due problem in this area of research.

In addition to ECG, the photoplethysmogram (PPG) signal has become an indispensable tool for detecting and diagnosing the blood oxygen saturation (SpO2), blood glucose, blood pressure, sleep apnea, etc., [47]. To speed-up and improve the quality of diagnosis, a few attempts have been made to acquire, monitor, and process multiple bio-signals (MBioSigs) such as ECG, PPG, ballistocardiogram (BCG), electromyogram (EMG) signals, respiration and body temperature [47,49,50-55]. Shared goals of all these developments are to produce a comprehensible snapshot of the patient and also to make it easier for the healthcare professionals to reach a conclusion. Yet, the area of compression of MBioSigs remains less-explored to date and needs the attention of the researchers.

Along with ECG, PPG and other biomedical signals, patient-specific confidential information such as age, gender, ethnic background and medical history, also plays an important role for proper diagnosis of the case. It is necessary to send such information along with the biosignals to the doctors. Steganography is the technique, which could be used to conceal confidential information of the patients inside the biosignal itself. However, only a few attempts have been made hitherto in this particular area of research [56-59] and needs to be explored further.

7. References

1. World Health Organization, Cardiovascular diseases (CVDs), Fact sheet No 317, March 2013.

2. S.K. Mukhopadhyay, S. Mitra, and M. Mitra, “A combined application of lossless and lossy compression in ECG processing and transmission via GSM-based SMS”, *Journal of Medical Engineering & Technology*, vol. 39, no. 2, February 2015, pp. 105-122.

3. A.L. Goldberger, “Clinical electrocardiography, a simplified approach”, Elsevier, Seventh Edition, 2006, USA.

4. A. Koski, “Lossless ECG encoding”, *Computer Methods and Programs in Biomedicine*, vol. 52, iss. 1, January 1997, pp. 23-33.

5. S.K. Mukhopadhyay, S. Mitra, and M. Mitra, “A lossless ECG data compression technique using ASCII character encoding”, *Computers and Electrical Engineering*, vol. 37, iss. 4, July 2011, pp. 486-497.

6. M.E. Hameed, M.M. Ibrahim, N.A. Manap, and A.A. Mohammed, “A lossless compression and encryption mechanism for remote monitoring of ECG data using Huffman coding and CBC-AES”, *Future Generation Computer Systems*, vol. 111, iss. 10, October 2020, pp. 829-840.

7. T.H. Tsai and F.L. Tsai, “Efficient lossless compression scheme for multi-channel ECG signal processing”, *Biomedical Signal Processing and Control*, vol. 59, iss. 5, May 2020, pp. 1-8.

8. J.P. Abenstein and W.J. Tompkins, “A new data-reduction algorithm for real-time ECG analysis”, *IEEE Transactions on Biomedical Engineering,* vol. BME-29, no. 1, January 1982, pp. 43-48.

9. S.K. Mukhopadhyay, S. Mitra, and M. Mitra, "An ECG signal compression technique using ASCII character encoding", *Measurement*, vol. 45, iss. 6, July 2012, pp. 1651-1660.

10. J.R. Cox, F.M. Nolle, H.A. Fozzard, and G.C. Oliver, "AZTEC, a preprocessing program for real time rhythm analysis", *IEEE Transactions on Biomedical Engineering*, vol. BME-15, iss. 2, April 1968, pp. 128-129.

11. J.L. Ma, T.T. Zhang, and M.C. Dong, "A novel ECG data compression method using adaptive Fourier decomposition with security guarantee in e-health applications", *IEEE Journal of Biomedical and Health Informatics*, vol. 19, no. 3, May 2015, pp. 986-994.

12. D. Sadhukhan, S. Pal, and M. Mitra, "Electrocardiogram data compression using adaptive bit encoding of the discrete Fourier transforms coefficients", *IET Science, Measurement & Technology*, vol. 9, iss. 7, October 2015, pp. 866-874.

13. S.K. Mukhopadhyay, M.O. Ahmad, and M.N.S. Swamy, "SVD and ASCII character encoding-based compression of multiple biosignals for remote healthcare systems", *IEEE Transactions on Biomedical Circuits and Systems*, vol. 12, no. 1, February 2018, pp. 137-150.

14. P. Bera, R. Gupta, and J. Saha, "Preserving abnormal beat morphology in long-term ECG recording: an efficient hybrid compression approach", *IEEE Transactions on Instrumentation and Measurement*, vol. 69, no. 5, May 2020, pp. 2084-2092.

15. C.J. Deepu and Y. Lian, "A joint QRS detection and data compression scheme for wearable sensors", *IEEE Transaction on Biomedical Engineering,* vol. 62, no. 1, January 2015, pp. 165-175.

16. G. Nave and A. Cohen, "ECG compression using long-term prediction", *IEEE Transaction on Biomedical Engineering*, vol. 40, no. 9, September 1993, pp. 877-885.

17. A. Pandey, B.S. Saini, B. Singh, and N. Sood, "Quality controlled ECG data compression based on 2D discrete cosine coefficient filtering and iterative JPEG2000 encoding", *Measurement*, vol. 152, iss. 4, February 2020, pp. 1-15.

18. J. Chagnon and L.R. Neira, "Mixed-transform based codec for 2D compression of ECG signals", *Biomedical Signal Processing and Control*, vol. 62, iss. 8, September 2020, pp. 1-4.

19. R. Gupta, "Quality aware compression of electrocardiogram using principal component analysis", *Journal of Medical Systems*, vol. 40, no. 112, March 2016, pp. 1-11.

20. C.S. Pattichis, E. Kyriacou, S. Voskarides, M.S. Pattichis, R. Istepanian, and C.N. Schizas, "Wireless telemedicine systems: an overview", *IEEE Antennas and Propagation*, vol. 44, iss. 2, April 2002, pp. 143-153.

21. B.S. Kim and S.K. Yoo, "Performance evaluation of wavelet-based ECG compression algorithms for telecardiology application over CDMA network", *Medical Informatics and Internet in Medicine*, vol. 32, iss. 3, January 2007, pp. 177-189.

22. R.S.H. Istepanian and A.A. Petrosian, "Optimal zonal wavelet-based ECG data compression for a mobile telecardiology system", *IEEE Transactions on Information Technology in Biomedicine*, vol. 4, no. 3, September 2000, pp. 200-211.

23. R.H. Istepanian, B. Woodward, E. Gorilas, and P. Balos, "Design of mobile telemedicine systems using GSM and IS-54 cellular telephone standards", *Journal of Telemedicine and Telecare*, vol. 4, iss. 1, March 1998, pp. 80-82.

24. M. Siraj and K.A. Bakar, "Minimizing interference in wireless mesh networks based telemedicine systems", *Journal of Computer Science*, vol. 8, no. 8, July 2012, pp. 1263-1271.

25. C. Otto and A. Pipe, "Remote, mobile telemedicine: The satellite transmission of medical data from Mount Logan", *Journal of Telemedicine and Telecare*, vol. 3, iss. 1, June 1997, pp. 84-85.

26. S.K. Mukhopadhyay, S. Mitra, and M. Mitra, "ECG signal compression using ASCII character encoding and transmission via SMS", *Biomedical Signal Processing and Control*, vol. 8, iss. 4, July 2013, pp. 354-363.

27. C.P.D. Souza, T.P. Pereira, and R.C.S. Freire, "Electrocardiogram by mobile phone: a compression method for SMS", in: *XIX IMEKO World Congress, Fundamental and Applied Metrology*, September 6–11, 2009, Lisbon, Portugal, 2009, pp. 1707-1710.

28. M. Mitra, J. N. Bera, and R. Gupta, "Electrocardiogram compression technique for global system of mobile-based offline telecardiology application for rural clinics in India", *IET Science, Measurement and Technology*, vol. 6, iss. 6, November 2012, pp. 412-419.

29. R. Gupta, J.N. Bera, and M. Mitra, "An intelligent telecardiology system for offline wireless transmission and remote analysis of ECG", *Journal of Medical Engineering and technology*, vol. 36, iss. 7, July 2012, pp. 358-365.

30. R. Gupta, J. N. Bera, and M. Mitra, "A bi-phase enebled serial acquisition system for remote processing of digitized ECG", *Computers and Electrical Engineering*, vol. 38, iss. 1, January 2012, pp. 68-74.

31. H. Ozkan, O. Ozhan, Y. Karadana, M. Gulcu, S. Macit, and F. Husain, "A portable wearable tele-ECG monitoring system", *IEEE Transactions on Instrumentation and Measurement*, vol. 69, no. 1, January 2020, pp. 173-182.

32. A. Alesanco and J. Garcia, "Clinical assessment of wireless ECG transmission in real-time cardiac telemonitoring", *IEEE Transactions on Information Technology in Biomedicine*, vol. 14, no. 5, September 2010, pp. 1144-1152.

33. S. Raj, "An efficient IoT-based platform for remote real-time cardiac activity monitoring", *IEEE Transactions on Consumer Electronics*, vol. 66, no 2, May 2020, pp. 106-114.

34. S.K. Mukhopadhyay and R. Gupta, "Data compression in health monitoring", Chapter 3, H*ealth Monitoring Systems: An Enabling Technology for Patient Care*, CRC Press, Taylor & Francis, November 2019, New York.

35. Y. Zigel, A. Cohen, and A. Katz, "The weighted diagnostic distortion (WDD) measure for ECG signal compression", *IEEE Transactions on Biomedical Engineering*, vol. 47, iss. 11, November 2000, pp. 1422-1430.

36. S.K. Mukhopadhyay, M.O. Ahmad, and M.N.S. Swamy, "An ECG compression algorithm with guaranteed reconstruction quality based on optimum truncation of singular values and ASCII character encoding", *Biomedical Signal Processing and Control*, vol. 44, iss. 6, July 2018, pp. 288-306.

37. B.A. Rajoub, "An efficient coding algorithm for the compression of ECG signals using the wavelet transform", *IEEE Transactions on Biomedical Engineering*, vol. 49, iss. 4, April 2002, pp. 355-362.

38. M. L. Hilton, "Wavelet and wavelet packet compression of electrocardiograms", *IEEE Transactions on Biomedical Engineering*, vol. 44, iss. 5, May 1997, pp. 394-402.

39. R.S.H. Istepanian, L.J. Hadjileontiadis, and S.M. Panas, "ECG data compression using wavelets and higher order statistics methods", *IEEE Transactions on Information Technology in Biomedicine* , vol. 5, iss. 2, June 2001, pp. 108-115.

40. Z. Lu, D.Y. Kim, and W.A. Pearlman, "Wavelet compression of ECG signals by the set partitioning in hierarchical trees algorithm" *IEEE Transactions on Biomedical Engineering*, vol. 47, no. 7, July 2000, pp. 849–856.

41. I.T. Jollife, Principal component analysis. Springer, New York, 2002.

42. A. Skodras, C. Christopoulos, and T. Ebrahimi, "The JPEG 2000 still image compression standard", *IEEE Signal Processing Magazine,* vol. 18, iss. 5, September 2001, pp. 36-58.

43. J. Pan and W.J. Tompkins, "A real-time QRS detection algorithm", *IEEE Transactions on Biomedical Engineering*, vol. 32, iss. 3, March 1985, pp. 230-236.

44. Myant. [Online]. Available: https://myant.ca/latest-developments, accessed in September 2020.

45. M.S. Manikandan and S. Dandapat, "Wavelet energy based diagnostic distortion measure for ECG", *Biomedical Signal Processing and Control,* vol. 2, no. 2, April 2007, pp. 80-96.

46. Physionet. [Online]. Available: https://physionet.org/about/database, accessed in September 2020.

47. R. Munnoch and P. Jiang, "A personal medical device for multi-sensor, remote vital signs collection in the elderly", *Proc. of Science and Information Conference*, 28-30 July 2015, London, UK, pp. 1122-1131.

48. L. Yan, J. Pettine, S. Mitra, S. Kim, D. W. Jee, H. Kim, M. Osawa, Y. Harada, K. Tamiya, C.V. Hoof, and R.F. Yazicioglu, "A 13 µA analog signal processing IC for accurate recognition of multiple intra-cardiac signals", *IEEE Transactions on Biomedical Circuits and Systems*, vol. 7, no. 6, December 2013, pp. 785-795.

49. C. Bruser, C.H. Antink, T. Wartzek, M. Walter, and S. Leonhardt, "Ambient and unobtrusive cardiorespiratory monitoring techniques", *IEEE Reviews In Biomedical Engineering*, vol. 8, March 2015, pp. 30-45.

50. Sandberg, R. Bailon, D. Hernando, P. Laguna, and J. P. Martinez, "Prediction of intradialytic hypotension using PPG and ECG", *Proc. of Computing in Cardiology Conference*, 22-25 September 2013, Zaragoza, Spain, pp. 1227-1230.

51. H. J. Baek, G.S. Chung, K.K. Kim, and K.S. Park, "A smart health monitoring chair for nonintrusive measurement of biological signals", *IEEE Transactions on Information Technology In Biomedicine*, vol. 16, no. 1, January 2012, pp. 150-158.

52. J.S. Lee, G.S. Chung, H.J. Beak, Y.G. Lim, J.S. Lee, D.U. Jeong, and K.S. Park, "A new approach of unconstrained sleep monitoring and Pulse Arrival Time extraction using PPG pillow and CC-ECG electrode system", *Proc. of 9th Inter. Conference on Information Technology and Applications in Biomedicine*, Larnaca, Cyprus, 4-7 November 2009, pp. 1-3.

53. W Karlen, A. Garde, D. Myers, C. Scheffer, J.M. Ansermino, and G.A. Dumont, "Estimation of respiratory rate from photoplethysmographic imaging videos compared to pulse oximetry", *IEEE Journal of Biomedical and Health Informatics*, vol. 19, no. 4, July 2015, pp. 1331-1338.

54. W. Karlen, C. Mattiussi, and D. Floreano, "Sleep and wake classification with ECG and respiratory effort signals", *IEEE Transactions on Biomedical Circuits and Systems*, vol. 3, no. 2, April 2009, pp.71-78.

55. A.M.R. Dixon, E.G. Allstot, D. Gangopadhyay, and D.J. Allstot, "Compressed sensing system considerations for ECG and EMG wireless biosensors", *IEEE Transactions on Biomedical Circuits and Systems*, vol. 6, no. 2, April 2012, pp. 156-166.

56. A. Ibaida and I. Khalil, "Wavelet-based ECG steganography for protecting patient confidential information in point-of-care systems", *IEEE Transactions on Biomedical Engineering,* vol. 60, no. 12, December 2013, pp. 3322- 3330.

57. S.E. Jero and P. Ramu, "Curvelets-based ECG steganography for data security", *Electronics Letters*, vol. 52 no. 4, February 2016, pp. 283-285.

58. S.E. Jero, P. Ramu, and R. Swamynathan, "Imperceptibility-robustness tradeoff studies for ECG steganography using continuous ant colony optimization", *Expert Systems with Applications*, vol. 49, iss. 1, May 2016, pp. 123-135.

59. S.K. Mukhopadhyay, M.O. Ahmad, and M.N.S. Swamy, "Compression of steganographed PPG signal with guaranteed reconstruction quality based on optimum truncation of singular values and ASCII character encoding", *IEEE Transactions on Biomedical Engineering,* vol. 66, no. 7, July 2019, pp. 2081-2090.