# A Survey on different Compression Techniques for ECG Data Reduction

Sakshi
Department of Computer Engineering
Punjabi University, Punjab
Patiala, India

Nirvair Neeru
Department of Computer Engineering
Punjabi University, Punjab
Patiala, India

## ABSTRACT
Electrocardiogram (ECG) is the technique that is used to record the electrical signal of the heart over a time interval by using the electrodes, positioned on a patient's body. The signals collected from the body needs to be processed and compressed before directing to monitoring center. Electrocardiogram (ECG) data compressions minimize the necessities of storage to generate a more proficient tele-cardiology system for the cardiac exploration and diagnosis. This paper focus on the evaluation of several compression schemes for ECG data compression and also provides the comparison of the various ECG compression techniques such as Turning Point, Delta Coding, AZTEC, CORTES, DCT etc. in terms of different performance metrics like Compression Ratio (CR), Percent Mean Square Difference (PRD) and Quality Score (QS).

## Keywords
ECG signal, Compressive Sensing, Time domain techniques, Wavelet based techniques.

## 1. INTRODUCTION
ECG is referred as the Electrocardiography derived from the Greek letter Kardia which means Heart. This process has done through the intrigues of electrodes on the patient's body to monitor the electric motions of the heart with respect to time. It is being used to understand the functionality of the heart regarding signals. These electrodes, attached with the human body senses the electrical variations because of the depolarizing of heart muscles concerning each heartbeat happening in the skin [1]. In the existing methods, total 10 electrodes were employed that was attached with the 12 number of lead ECG on the chest of the patient which continuously monitors the magnitude of the heart from the different 12 angles through the 12 different leads. The variations in the signals were made through the electric rays which generates a graph considered as ECG. The whole process is done through a special kind of device which continuously monitors the variations in the patients' body with respect to a specific interval of time [2].This device is dedicatedly works for the detection of heart diseases. The ECG generated through this device is based upon the electrical variations happen in the body of the patient. The ECG test does not affect the human body as it is harmless but the people has a belief that this process leaves some electrical current on the body which is not true.

ECG is not only responsible for the functionality of the heart but for the structure as well. Additionally, it estimates the rhythm and heartbeat rate which makes it possible to calculate the size and the location of the elements [3]. In case of any injury or damage to the heart, elements can also be identified through the ECG.

Other main purposes of ECG are listed in the below points such as [4]:

- ECG is used to monitor or detect the coronary heart disease as it identifies weather the flow of the blood to the heart muscles is either low or good.
- It also detects the speed of the heartbeat while detecting the Arrhythmia.
- To identify the heart failure.
- To detect the Cardio-myopathy, Cogenital heart defects and heart value disease.

The above purposes of the Electrocardiography can be summed up as it monitors the speed of the heartbeat i.e. low, medium or fast. Moreover, it is also used to detect several heart diseases such as:

- pain in chest
- heart attacks
- Difficulty in breathing
- Swelling in the surrounding areas of the heart
- Dizziness
- Hypertrophied

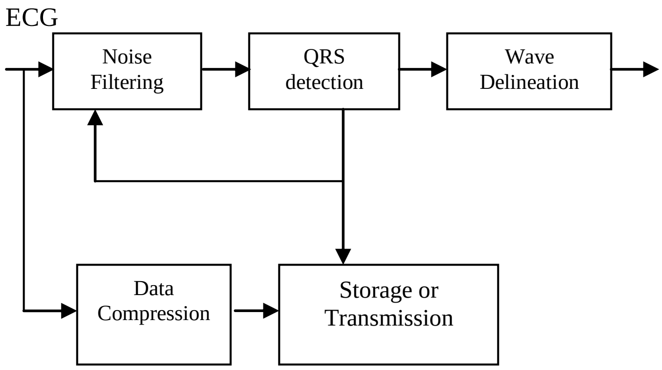


**Fig 1 Basic ECG signal Processing[12]**

The figure 1 describes the ECG signal process that is initiated by filtering, then its QRS waves are detected and at the end the transmission is done [5]. The wireless ECG system is superior to the current health monitoring systems due to the following reasons:

- It does not limit the mobility of the patient.
- Monitoring of the ECG signals can be done outside the hospitals or medical centers.

This paper reviewed the Compressed Sensing with the ECG signal on wireless body sensor nodes.

## 2. RELATED WORK

1. **Xiaoxiao Wang et al [2]** A new electrocardiogram (ECG) compression technique on the basis of the combination of the empirical mode decomposition (EMD) and the wavelet transform was represented. The steps followed by the suggested technique are:

***EMD and IMF remixing:*** In the projected methodology, the ECG signal was first disintegrated by the EMD for every 1200 samples of a frame. The first one or two IMF was added up as the first mixed function and the other constituents were added together as the second mixed function.

***Feature points extraction and DWT:*** The extreme of the first mixed function was documented for reconstruction, and the original function can be rebuilt through cubic spline fitting. The error between the original and the reconstructed mixed function of each frame was computed to enhance the reconstruction accuracy.

***Dead zone quantization:*** The uniform scalar dead zone quantization was applied to the feature points of the first mixed function and the wavelet coefficients. The quantiser can be defined by the following equations:

$$I_k = \begin{cases} (-3\delta, -T), & if\ k = -1 \\ (-T, T), & if\ k = 0 \\ [T, 3\delta), & if\ k = 1 \\ [(2k-1)\delta, (2k+1)\delta), & otherwise \end{cases} \quad \text{…………(1)}$$

$$R_k = \begin{cases} 0, & \text{if k} = 0 \\ k\Delta, & if\ k = \pm 1, \pm 2, \ldots \end{cases} \quad \text{....................(2)}$$

***Feature points and wavelet coefficients coding:*** The locations of the feature points were first coded by the run length coding, then the Huffman coding technique was applied to both the run length codes and the values of the feature points.

The algorithm was easy to implement and required no prior knowledge of the signal. Results demonstrated that the proposed method was better than other DWT-based and EMD-based ECG compression techniques.

2. **Jiali Ma et al. [3]** offered a novel electrocardiogram (ECG) compression methodology for e-health applications by adapting Fourier decomposition (AFD) algorithm hybridized with symbol substitution (SS) technique. The compression comprised of two stages: In 1st stage AFD implemented effective lossy compression with high fidelity; at 2nd stage SS executed lossless compression for the enhancement and built-in data encryption which was pivotal for e-health. Validated with 48 ECG records from MIT-BIH arrhythmia benchmark database, the suggested process attained average compression ratio (CR) of 17.6 to 44.5 and percentage root mean square difference (PRD) of 0.8% to 2.0% with a highly linear and robust PRD-CR relationship, pushing forward the compression performance to an available region. As such, this work delivered an attractive candidate of ECG compression technique for pervasive e-health applications. In the below section, mathematical basis of the proposed AFD algorithm is represented:

***Mathematical Foundation of AFD Algorithm***
AFD is based on the modified TM system $\{B_n\}$ as given below:

$$B_n(z) = \frac{1}{\sqrt{2\pi}} \frac{\sqrt{1-|a_n|^2}}{1-\bar{a}_n z} \prod_{k-1}^{n-1} \frac{z-a_k}{1-\bar{a}_k z},\ n = 1,2, \ldots \text{…..(3)}$$

Where $a_n$ is a complex number adaptively chosen inside the open unit disc $\mathbb{D}$ ($\mathbb{D} = \{z \in \mathbb{C}: |z|<1\}$), $\mathbb{C}$ denotes the complex plane, and $z$ is the boundary of $\mathbb{D}$ described as $z = \exp(it)$, $t \in [0, 2\pi)$. For any $\{a_n\}$ sequence in $\mathbb{D}$, the modified TM system $\{B_n\}$ is proved to be orthogonal.

3. **Yang He et al [4]** proposed the flexibility and reconstruction quality issue happened in traditional CS-based ECG signal processing. One adaptive ECG compression technique inspired by closed-loop control theory was proposed, in which the compression ratio can be adjusted as per both real-time reconstruction error and previous knowledge support. The results of simulation shown the proposed scheme can increase the compression performance of 10.83% as compared with traditional CS-based schemes.

Here is the brief overview of above proposed technique as mentioned in this paper:

***PE: percentage root-mean-square difference (PRD) estimation***
In control system, the controller makes sense by comparing output of measured object with the reference value and then uses their D-value to drive actuator. Encouraged by this idea, an evaluation of real-time monitoring quality was drawn by comparing real-time reconstruction error with observing demand in standard. In order to compute the difference between the original and reconstructed signal, the indicator PRD was used.

Compressed signal was transferred to the mobile terminal together with beacon information and then real-time PRD can be evaluated via formula expressed below:

$$PRD_l = \sqrt{\frac{\sum_{i=1}^{l}(x_i - \tilde{x}_i)^2}{\sum_{i=1}^{l} x_i^2}} \times 100\% \text{..............................(4)}$$

4. **A. Bendifallah et al [5]** shown the progress of a discrete cosine transform (DCT)-based technique for electrocardiogram (ECG) compression. The use of a block based DCT connected to a uniform scalar dead zone quantiser and arithmetic coding presented worthy results, ensuring that the proposed strategy demonstrates the competitive performances as compared with the most widespread compressors used for ECG compression. Below are the steps followed by this proposed work:

***DCT and dead zone quantiser:*** The ECG signal (after eliminating its mean value) was segregated in sequential blocks of 64 sample lengths for each, after which, the DCT transform was applied to each block. The DCT transform had the feature to offer a large number of tiny coefficients which were zeroed after the quantization step. The dead zone quantiser applied to DCT coefficients can be described by the following equations:

$$I_k = \begin{cases} (-3\delta, -T), & if\ k = -1 \\ (-T, T), & if\ k = 0 \\ [T, 3\delta), & if\ k = 1 \\ [(2k-1)\delta, (2k-1)\delta), & otherwise \end{cases} \quad \text{……(5)}$$

$$R_k = \begin{cases} 0, & \text{if k} = 0 \\ \pm k\Delta, & if\ k = \pm 1, \pm 2, \ldots \end{cases} \quad \text{...............(6)}$$

It was validated that for a decent quality reproduction, the decision intervals are correlated to the dead zone length T by a relation of the form D ¼ aT, where a is a parameter to be properly determined.

**Table 1 Summary of Literature Review**

| S. No | Author | Proposed Work | Technique used |
|---|---|---|---|
| 1 | Xiaoxiao Wang et al [2] | A novel electrocardiogram (ECG) compression system based on the combination of the empirical mode decomposition (EMD) and the wavelet transform was proposed to enhance the reconstruction accuracy | EMD and IMF remixing, Feature points extraction and DWT, Dead zone quantization, Feature points and wavelet coefficients coding |
| 2 | Jiali Ma et al [3] | A new electrocardiogram (ECG) compression methodology by AFD algorithm hybridized with SS technique was recommended for pervasive e-health applications | AFD (Adapting Fourier Decomposition) , SS (Symbol Substitution) |
| 3 | Yang He et al [4] | adaptive ECG compression technique encouraged by closed-loop control theory was suggested to enhance the compression performance | PE: percentage root-mean-square difference (PRD) estimation |
| 4 | A. Bendifallah et al [5] | The improvement of a discrete cosine transform (DCT)-based technique for electrocardiogram (ECG) compression was proposed ensuring competitive performances as compared with the most widespread compressors used for ECG compression | DCT and dead zone quantiser |

## 3. CLASSIFICATION OF ECG SIGNALS

The classification of the ECG signal becomes a necessity as it helps for identifying the data that needs to be reconstructed in order to diagnose the disease. This classification will help the Cardiologist for analyzing, whether the patient's condition is normal or not. Consequently, the patient's heart condition can be divided into two main categories such as normal and abnormal. An algorithm termed as A*OMP is used to reconstruct the stored as well as compressed ECG signal for the diagnoses.

The stored and compressed measurements are regenerated to original ECG signal through the algorithm "A*OMP" in order to analyze any cardiac arrhythmia [6]. The region of interest represents the swift depolarization in the right and the left ventricles, therefore it permits the ECG to record the electrical potential generated. Cardiac arrhythmia is the situation in which the heart's sinus rhythm is disturbed. The heart rhythm is characteristically monitored by ECG where the QRS complex which is connected with the excitation of ventricles, plays vital role for the reorganization of the cardiac arrhythmias. The unusual situations contain uneven peak value, irregular distance between peaks of the ECG signal and unstable range of QRS complex beyond its expected span. The distance between contiguous QRS complexes and RR interval regulates the rhythm of heart rate i.e. regular or irregular. The period between two R peaks has duration of 0.6 to 1.2 seconds [7]. If the rhythm is irregular, it is generally associated with atrial flutter and a trial fibrillation. The typical resting heart rate is between 50-100 bpm. The QRS complex has duration of80-120 m-s, if the QRS complex extends beyond this range it could activate hypo-kalemia which may sometimes provoke the cardiac arrhythmias. Also the amplitude of R peak calculated from the V5 lead (MIT-BIH ECG database) [8] generally lies below the value of 2.6 mV. When any of the above parameters surpasses their range, the ECG signal has been classified as abnormal.

## 4. COMPRESSIVE SENSING OF ECG SIGNALS

The signal is sampled and simultaneously compressed in the recent Emerging technique of CS. The biomedical signal is sparse in terms of either a non-zero coefficients number or a number of non-zero blocks. The compressed sensing theory is to recreate the original signal from a small number of selected observations and directly measure compressed illustration. To accomplish the much lower sampling rate for a sparse signal, the theory of CS was offered recently. CS theory represents that many biomedical signals are sparse or, in practice near sparse and can be compressed and improved by a small number of random linear measurements. In other words, the small number of random measurements contains adequate information to process, transmit, and recuperate (fewer measurements instead of vast samples). The CS theory can decrease the number of bits of the information; as a result, it raises the life of the wireless nodes by reducing the power consumption. The data size is condensed by applying the CS theory, fewer bandwidths are necessary to transmit data, and less power consumption is needed to process the data [9]. Decreased number of attained samples is advantageous for the WBAN. It moderates the necessities imposed on sensor storage and processing abilities. Compressed sensing has benefits as:

It offers easier hardware implementations for the encoder, low computational difficulty, less traffic volume and less time delay and it enables to recreate the sparse signal from less number of linear projections.

Exploiting sparsity is the base of compressed sensing. Sparse signals can be represented as a blend of a small number of projections on a certain basis (That must be incoherent to the original basis). So the same signal can be represented with a lesser amount of data because of sparsity, still permitting the precise reconstruction [10]. One would obtain a large amount of data in uncompressed sensing techniques, calculates a suitable basis and projections on it and then transfer these projections and the basis used. This is waste of resources since a lot of data points are primarily collected and then transferred. In compressed sensing, a basis is selected that will approximately symbolize any input sparse signal, as long as there is some acceptable margin of error for reconstruction.

The CS theory switches the conventional sampling and reconstruction procedure with a common random linear measurement procedure and an optimization structure in order to improve the original signal from a small number of random measurements.

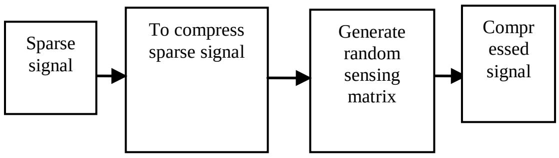


**Fig. 2 CS Transmitter [14]**

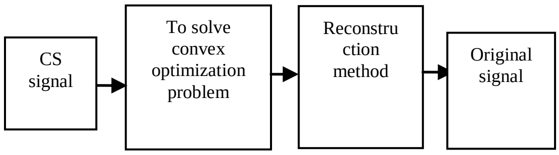


**Fig. 3 CS Receiver [14]**

Compressive sensing is signal processing framework where the sparse signal is used and rebuilds it from the partial measurements, which have inadequate amount of information and can be attained if the signal is in sparse demonstration with an ortho-normal basis. CS is specified to the Electrocardiogram (ECG) signal for data condensation in WBN network. Wavelet compressed signal is used for the multi-lead ECG signal [11]. Data assembling system that is based on compressed sensing with wireless bio-sensors is used for bio-signals like ECG and EEG etc. In an ECG signal, vital diagnostic information such as P-wave, QRS-complex and T-wave is represented. These mechanisms may hold pathological information. CS based signal processing does not alter these information. Sparse representation is very essential condensed sensing of signal. Compression is essential for minimizing the storage space and broadcast times. Hence, ECG data compression is needed for effective storage and transmission of signal for the applications of telemedicine. CS has some significant benefits such as:

1. It makes hardware implementations easy for the encoder.
2. The position of the largest is not requires to be encoded.
3. It allows the regenerating of sparse or compressible signals from a few linear projections.

# 5. APPLICATION OF COMPRESSED SENSING IN WBAN

As a detachment of WSNs contains wireless sensor nodes attached to or on the human body for fitness monitoring, intellectual emergency care management systems, intensive concern, surgical treatment, diagnosis purposes and universal wireless healthcare applications by affecting wireless communication technologies to BANs or Personal area network for carrying the biomedical records. In the WBAN, the biomedical wireless sensors assemble and broadcast the patient's records to medicinal centers using a gateway. This increases the quality of patient care and competence. WBAN decrease the expenditure of health care as they permit the isolated monitoring of numerous patients concurrently [12]. The CS theory, as a developing data compression methodology, allows few essential constraints in WBAN. Medicinal applications of WBAN based on CS theory encompasses the constant waveform sampling of the biomedical signals, monitoring of the essential signal information and low rate power remote control of medical devices.

Wireless sensors compress the biomedical signals. The condensed biomedical data gathered and then transmitted to the access point (APs). The APs improves the compressed biomedical data for diagnostic and therapeutic purposes. The acknowledged vector in GW can be written as:

$$[\mathbb{S}]_{M\times 1} = [\emptyset]_{M\times N}[X]_{N\times 1}\ldots\ldots\ldots\ldots\ldots(7)$$

The CS in WBANs can offer an advanced transmission, a lesser time delay and better possibility for the achievement of data transmission [13]. CS theory in WBANs is provided with the low sampling rate and power utilization.

# 6. TECHNIQUES FOR ECG COMPRESSION

Generally, ECG compression can be categorized into lossy and lossless methods [7]. The lossless compression assures the reliability of reassembled data while negotiated compression ratio (CR), with nearly 0% reconstruction error. Lossy compression on the other hand, is having great CR with fluctuating level of reconstruction error [14].

ECG signal compression systems broadly fall into three groupings of direct method, transformation method and parameter extraction method [15]. The direct data compression method flexibly evaluates and diminishes data points in the time domain and the example contains turning point (TP), amplitude zone time epoch coding (AZTEC), Upgraded altered AZTEC technique, coordinate reduction time encoding system (CORTES), SLOPE [16], the delta algorithm and the Fan algorithm. The transformation technique analyzes the energy distribution by transforming the time domain to some other domain and example contains Fourier transform, Fourier descriptor, the discrete cosine transform (DCT), DCT with revised stages and wavelet transform, and the compressed sensing [17]. The parameter extraction method is based upon leading feature extraction from raw signal; examples involve neural based or syntactic methods [18], peak picking and linear prediction technique [19]. The other approaches for compression includes ASCII based encoding for incorporation of ECG data as ASCII character in current technology [20].

## 6.1 Direct Time-Domain Techniques:

Direct procedures are based on the extraction of a subset of the important samples. Direct time-domain ECG compression technologies have proficient performance in terms of processing speed and CR. The redundancies existing were directly explored by these techniques in the ECG samples. Direct compression method can base on three techniques: tolerance comparison Compression, differential pulse code modulation (DPCM), and entropy coding [21]. Next, the substantial work that has been focused towards direct ECG compression methods is discussed.

- AZTEC Technique
- TP
- CORTES
- FAN and SAPA
- Improved Modified AZTEC
- Delta Coding

## 6.2. Transform-Domain Techniques:

The application of linear orthogonal transformation performs transformation based ECG compression techniques to ECG samples. Therefore, novel samples of ECG are exposed to a conversion and the compression is performed in the completely new domain like Fourier transform (FT), DCT and wavelet etc [21]. These systems pose greater CR than direct systems and are unaffected to noise present in ECG signals.

- FT
- DCT
- Wavelet Domain

## 6.3 Parameter Extraction Techniques:

These are irretrievable procedures which maintain the specific characteristics or parameters of the ECG signals. The parameter extraction technique is based upon the dominant feature extraction from raw ECG signal; examples contain neural based or syntactic processes, peak picking and linear prediction technique [21].

- Peak Picking
- Long Term

The table 2 represents the comparison between different ECG compression techniques such as TP, Peak Picking, AZTEC, CORTES etc. on the basis of their result performances or features.

**Table 2 Comparison between ECG compression techniques[20]**

| Compression Technique | Findings |
|---|---|
| AZTEC | Poor P and T fidelity |
| TP | Sensitive to sampling frequency |
| CORTES | Sensitive to sf and Poor P fidelity |
| FAN/SAPA | High Fidelity |
| Peak Picking with entropy coding | Limited Results |
| DPCM-Delta coding with Threshold | Sensitive to SF and Quantization |
| Gradient Difference | Simple and High Fidelity |

# 7. PERFORMANCE EVALUATION PARAMETERS AND COMPARISON

The authentication of an ECG compression method can be judged by compression efficiency with error criterion. The capability of compression technique is measured by these parameters to rebuild the signal and to preserve the appropriate information.

## 7.1 Compression Ratio (CR)

It is described as the ratio of the original signal range and compressed signal range. The Compression ratio gives information about the degree by use of which the compression technique eliminates the redundant data. Higher the Compression ratio, less number of bits needed to store or transfer the data which can be mentioned as in given equation (2).

$$CR = \frac{Bo}{Bc} \quad \dots\dots\dots (8)$$

Where, Bo is the total number of bits that are requisite to represent original data and Bc indicates the total number of bits required to present compressed data.

## 7.2 Percent Mean Square Difference (PRD)

It computes the error between original with recreated signal, and is represented by using equation (3).

$$PRD(\%) = 100 \times \frac{\sqrt{\sum_{N=1}^{N}(Xs(n) - Xr(n))^2}}{\sum_{N=1}^{N}(Xs(n))^2} \quad \dots\dots\dots (9)$$

Where N is the number of data samples, Xs (n) is the original signal and Xr (n) is the reconstructed signal.

## 7.3 Quality Score (QS)

It is the ratio of CR and PRD which measures the whole performance of the compression techniques, and is provided by using equation (4)

$$QS = \frac{CR}{PRD} \quad \dots\dots\dots (10)$$

**Table 3 Performance comparison of different ECG compression techniques [23]**

| Compression Technique | CR | PRD | QS |
|---|---|---|---|
| AZTEC | 10 | 28 | 0.3571 |
| Improved modified AZTEC | 2.76-9.91 | 4.54-7.99 | 0.6079-1.24 |
| TP | 2 | 5.1 | 0.392 |
| CORTES | 4.8 | 7.0 | 0.685 |
| FAN and SAPA | 3.0 | 4.0 | 0.75 |
| SPIHT | 8 | 1.18 | 6.779 |
| SLOPE | 4.8 | 7.0 | 0.685 |
| Quantized DCT coefficients (Min CR) (Max CR) | 6.2 10.9 | 1.5 3 | 4.13 3.63 |
| Perceptual Masks | 3.5 | 1.24 | 2.822 |
| USZZQ and Huffman coding | 11.06 | 2.73 | 4.05 |

# 8. CONCLUSION AND FUTURE SCOPE

This paper provides an analysis of ECG compression methods (AZTEC, Delta Coding, TP, Wavelet Domain etc.), with their performance comparisons on the basis of various metrics such as Compression Ratio (CR), Percent Mean Square Difference (PRD) and Quality Score (QS). Several previous related research articles have been studied in this paper and it is analyzed from this study that wavelet transform based techniques are more effective and powerful than traditional techniques in terms of lossless data compression, because wavelet based techniques offer easy transformation and compression of data without any losses. Future guidelines for research may involve the incorporation of DWT (Discrete Wavelet Transform) technique that will further allow the reduction of the PRD (lossless compression) with enhanced CR and QS.

# 9. REFERENCES

[1] Hossein Mamaghanian,Nadia Khaled, David Atienza and Pierre Vandergheynst, "Compressed Sensing for Real-Time Energy-Efficient ECG Compression on Wireless Body Sensor Nodes", IEEE, transactions on Biomedical engineering, VOL. 58, NO. 9, Pp 2456-2466, 2011

[2] Xiaoxiao Wang, Zhijian Chen, Jiahui Luo, Jianyi Meng and Yin Xu, "ECG Compression based on combining of EMD and Wavelet Transform", IEEE, Electronics Letters, Vol 52, Issue 9, Pp 1588-1590, 2016

[3] Jiali Ma, TanTan Zhang and MingChui 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 9, Issue 3, pp 986-994, 2015

[4] Yang He,Wenbin Yu, Cailian Chen, Yiyin Wang and Xinping Guan, "Adaptive ECG Compression Scheme with prior knowledge support based on compressive sensing", IEEE, Pp 1-5, 2015

[5] A. Bendifallah, R. Benzid and M. Boulemden, "Improved ECG Compression Method using DCT", IEEE, Electronics Letter, Vol 47, Issue 2, Pp 87-89, 2011

[6] Andrianiaina Ravelomanantsoa, Hassan Rabah and Amar Rouane, "Simple and efficient compressed sensing encoder for WBAN", IEEE, Transaction on instrument and Measurements, Vol 63, Issue 2, Pp 2973-2982, 2014

[7] Bo Yu, Liuqing Yang and Chia-Chin Chong, "ECG Monitoring over Bluetooth: Data Compression and Transmission", IEEE, Pp 1-5, 2010

[8] Zhe Liu, Wenbin Yu, Cailian Chen , Bo Yang and Xinping Guan, "Adaptive Compression ratio estimation for categorified sparsity in real-time ECG Compression System", IEEE, Pp 9439-9444, 2016

[9] Ziran Peng, Guojun Wang, Huabin Jiang and Shuangwu Meng, "Research and Improvement of ECG Compression algorithm based on EZW", IEEE, Computer Methods and Programs in Biomedicine, Vol 145, Pp 157-166, 2017

[10] A. Singh,L.N. Sharma. and S. Dandapat, "Multichannel ECG data Compression using Compressed sensing in Eigen space", IEEE, Computer in Biology and medicine, Vol 73, Issue 1, pp 24-37, 2016

[11] Sibasankar Padhy L.N. Sharma and S. Dandapat, "Multilead ECG data Compression using SVD in multiresolution Domain", Biomedical Signal Processing and Control, Vol 23, Pp 10-18, 2016

[12] Giuliano Grossi, Raffaella Lanzarotti and Jianyi Lin, "High Rate Compression of ECG signals by an accuracy driven sparsity model relying on natural basis" Digital Signal Procession, Vol 45, pp 96-106, 2015

[13] Aymain Lbaida,Dhiah Al-Shammary and Ibrahim Khalil.,"Cloud enabled fractal based ECG compression on Wireless Body Sensor Networks", Future generation Computer System, Vol 35, Pp 91-101, 2014

[14] Boqiang Huang, Yuanyuan Wang and Jianhua Chen, "ECG Compression using context modeling arithmetic coding with dynamic learning vector scalar quantization", Biomedical Signal Processing and Control, Vol 8, issue 1, Pp 59-65, 2013

[15] Hong xin, Can-feng CHEN, Yan-ling WU, Pei-hua LI., "Decomposition and compression of ECG and EEG signals with sequence index coding methods based on matching pursuit", The journal of china universities and telecommunication, Vol 19, Issue 2, Pp 92-95, 2012

[16] K. Ranjeet,A. Kuamr and Rajesh K. Pandey, "ECG signal Compression using optimum wavelet filters Bank Base on Kaiser Window", Procedia Engineering, Vol 38, Pp 2889-2902, 2012

[17] Jianhua Chen,Fuyan Wang, Yufeng Zhang and Xinling Shi., "ECG Compression using uniform scalar dead zone quantization and conditional entropy coding", Vol 30, Issue 4, Pp 523-530, 2008

[18] Xingyuan Wang and Juan Meng, "A 2-D ECG compression algorithm based on wavelet transform and vector quantization", Digital Signal Processing, Vol 18, Issue 2, Pp 179-188, 2008.

[19] Anukul Pandey,Barjinder Singh Saini, Butta Singh and Neetu Sood, "A 2D electrocardiogram data compression method using a sample entropy based complexity sorting approach",Computer and Electrical Engineering, Vol 56, Issue 10, pp 30-45, 2016

[20] A. Rabee and I. Barhumi, "ECG signal classification using support vector machine based on wavelet multiresolution analysis" IEEE, Vol 2, No 5 ,Pp 1319 – 1323, 2012

[21] Sung-Nien Yu and Kuan-To Chou, "Combining Independent Component Analysis and Backpropagation Neural Network for ECG Beat Classification" IEEE, Pp 3090 – 3093, 2006

[22] M. Shahramand K. Nayebi, "Classification of multichannel ECG signals using a cross-distance analysis" IEEE, vol.3 , Pp 2182 - 2185 , 2011

[23] Butta Singh, Amandeep Kaur and Jugraj Singh, "A Review of ECG Data Compression Techniques", International Journal of Computer Applications, Vol. 116, No. 11, Pp. 39-44, April 2015