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An investigation towards efficient, lossless, multi-variance matrix-based cardiac data compression techniques

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***Abstract*—The Electrocardiogram (ECG) is a major source for the identification of cardiac diseases. The ECG signal has various components and features like P-QRS-T. The wave form with the PQRST components is used to identify the cardiac diseases and takes higher storage space. To reduce the space complexity, data compression techniques are recommended. Anumber of data compression techniques are available, and the efficiency of the compression approach is based on restoration efficiency. Moreover, the efficiency of compression algorithm depends on compression ratio achieved and restoration accuracy produced. This paper discusses about different methods of ECG data compression and performs a comparative study on various parameters. It alsopresents a lossless multi feature variance signal matrix approach to reduce the space complexity and improve the compression ratio.**

***Index Terms*— Electrocardiogram, Lossless compression, Wavelet Transform, Compression Ratio, Feature Variance Signal Matrix.**

I. Introduction

Human anatomy is more reactive to electric signals and each organ reacts to the electric signal. By passing electric signals to the human organs, the activity of the human organ can be traced. To monitor and read the activity of human heart the electro cardiogram is used. The ECG device has 12 electrodesplaced in different places of human body. A minimum electric signal is passed through the electrodes attached and the display unit attached to the device displays the waveform of heart function.

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II. ECG Signal

The ECG waveform produced by the device can be recorded and the recorded information takes higher storage space. The stored ECG waveform can be used to identify the presence of many cardiac diseases and could be used to compare with the others. Because of the space complexity of these recordings, the medical organizations require huge storage place. This also increases the storage cost of the waveforms. When the number of patients increases, the storage cost of them also hikes to different level. This increases the necessity of the waveform data to be compressed. Electrocardiography is a commonly used, non-invasive procedure for recording electrical changes in the heart. The records, which are called an electrocardiogram (ECG), show the series of waves that relate to the electrical impulses which occur during each beat of the heart. The results are printed on paper or displayed on a monitor. The waves in a normal record are named P, Q, R, S, and T and follow in alphabetical order.

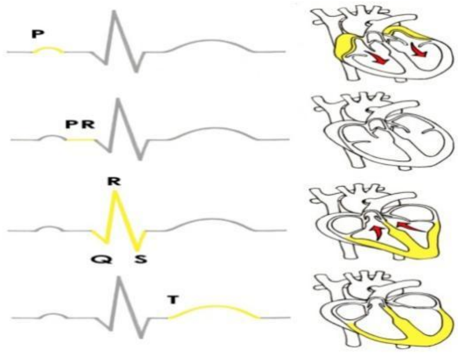

Fig. 1. ECG waveform

Fig 1 shows the snapshot of ECG waveform and the different components of ECG waveform. The number of waves may vary, and other waves could be present. The descriptions of P, Q, R, S, T wave are as follows :

P wave – it is important to remember that the P wave represents the sequential activation of the right and left atria, and it is common to see notched or biphasic Pwaves of right and left atrial activation,

PR interval – represents the time necessary to transferactivation from atria to ventricles.

QRS complex - the QRS complex is a structure on the ECG that corresponds to the depolarization of the ventricles. In addition, because the Purkinje system coordinates the depolarization of the ventricles, the QRS complex tends to look "spiked" rather than rounded, due to the increase in conduction velocity. A normal QRS complex is 0.06 to 0.10 sec (60 to 100 ms) in duration represented by three small squares or less.Any abnormality of conduction takes a longer time, and causes widened QRS complexes,

ST segment and T wave - in a sense, the term "ST segment" is a misnomer, because a discrete ST segment distinct from the T wave is usually absent. More often the ST-T wave is a smooth, continuous waveform beginning with the J-point (end of QRS), slowly rising to the peak of the T and followed by a rapid descent to the isoelectric baseline or the onset of the U wave. This gives rise to an asymmetrical T wave,

T wave - represents the repolarization (or recovery) of the ventricles. The interval from the beginning of the QRS complex to the apex of the T wave is referred to as the absolute refractory period. The last half of the T wave is referred to as the relative refractory period (or vulnerable period).

Arrhythmia detection program for an ambulatory ECG monitor [1], digitizes at the rate of 200 samples per second in order to retain QRS detail. A compression algorithm reduces the number of saved data points to one-half. After approximately 25 seconds of initialization, the software begins its search for the programmed arrhythmias. When the hardware R-wave detector finds an R wave, the program compares the time interval to the last R wave (R-R interval) both to previous R-R intervals. Thus, it senses a possible change in rhythm. When the program encounters an arrhythmia it signals an audible alarm. By checking a liquid crystal display, the patient can determine which condition initiated the alarm. Depending on the type of arrhythmia detected, the program retains 16 sec of data previous to or surrounding the moment of alarm for transmission to a central computer for physician evaluation. In addition a manual override switch permits the patient to save 16 sec of data whenever symptoms suggest cardiac involvement.

Heart Rate Monitoring and PQRST Detection Based on Graphical User Interface with Matlab [2], proposes a simple and dependable method to detect the P, Q, R, S and T values of an electrocardiogram (ECG) signal. This method is based on finding a mathematical relationship between the highest values (peaks and valleys) of the ECG waveform and time. This proposed method is exemplified by designing a graphical user Interface (GUI) by using MATLAB for detecting PQRST by using simple mathematical algorithm to get PQRST values and draw these values as ECG wave at the same time.

Detection of Fetal Heart Rate Through 3-D Phase Space Analysis From Multivariate Abdominal Recordings [3], novel three-stage methodology for the detection of fetal heart rate (fHR) from multivariate abdominal ECG recordings is introduced. In the first stage, the maternal R-peaks and fiducial points (maternal QRS onset and offset) are detected, using band-pass filtering and phase space analysis. The maternal fiducial points are used to eliminate the maternal QRS complexes from the abdominal ECG recordings. In the second stage, two denoising procedures are applied to enhance the fetal QRS complexes. The phase space characteristics are employed to identify fetal heart beats not overlapping with the maternal QRSs, which are eliminated in the first stage. The extraction of the fHR is accomplished in the third stage, using a histogram-based technique in order to identify the location of the fetal heart beats that overlap with the maternal QRSs.

III. HEART RATE DETECTION

Using the ECG waveform generated, the human heart rate can be computed. From the ECG waveform, different components can be extracted. Based on extracted features, the heart rate can be computed. A number of methods have been described earlier for the detection of heart rate.

In [4],ageneralized likelihood ratio test (GLRT) statistic is proposed for detection of heart rate turbulence (HRT), where a set of Karhunen-LoEve basis functions models HRT. The detector structure is based on the extended integral pulse frequency modulation model that accounts for the presence of ectopic beats and HRT. This new test statistic takes a priori information regarding HRT shape into account, whereas our previously presented GLRT detector relied solely on the energy contained in the signal subspace. The spectral relationship between heart rate variability (HRV) and HRT is investigated for the purpose of modeling HRV Noises present during the turbulence period, the results suggesting that the white noise assumption is feasible to pursue.

Adaptive Beat-to-Beat Heart Rate Estimation in Ballistocardiograms [5], present a novel algorithm for the detection of individual heart beats and beat-to-beat interval lengths in ballistocardiograms (BCGs) from healthy subjects. An automatic training step based on unsupervised learning techniques is used to extract the shape of a single heart beat from the BCG. Using the learned parameters, the occurrence of individual heart beats in the signal is detected. A final refinement step improves the accuracy of the estimated beat-to-beat interval lengths.

In Real-Time Automated Point-Process Method for the Detection and Correction of Erroneous and Ectopic Heartbeats [6], a novel point-process-based method is developed for real-time R-R interval error detection and correction. Given an R-wave event, we assume that the length of the next R-R interval follows a physiologically motivated, time-varying inverse Gaussian probability distribution. We then devise an instantaneous automated detection and correction procedure for erroneous and arrhythmic beats by using the information on the probability of occurrence of the observed beat provided by the model. In [7],a optimal heart rate estimation approach was identified by application of a variety of frequency estimation techniques and comparing results manually acquired values.

In Robust Sensor Fusion of Unobtrusively Measured Heart Rate [8],discussedan artifact detection is an essential preprocessing step to allow a reliable fusion. Second, the robust but computationally efficient median already provides good results; however, using a Bayesian approach, and a short time estimation of the variance, best results in terms of difference to reference heart rate and temporal coverage can be achieved.

Heart Rate Detection During Sleep Using a Flexible RF Resonator and Injection-Locked PLL Sensor [9], Novel nonintrusive technologies for wrist pulse detection have been developed and proposed as systems for sleep monitoring using three types of radio frequency (RF) sensors. The three types of RF sensors for heart rate measurement on wrist are a flexible RF single resonator, array resonators, and an injection-locked PLL resonator sensor. To verify the performance of the new RF systems, we compared heart rates between presleep time and postsleep onset time.

In [10], a phase-based algorithm based on a logarithmic method is developed which are applicable to UWB radars and suitable to real-time monitoring, is proposed to detect the phase variations of reflected pulses caused by the tiny cardiac motions. Compared with conventional FFT vital signs detection method, this algorithm demonstrates advantage in respiration harmonics suppression and avoidance of intermodulation between respiration and heartbeat signals.

IV. ECG Data Compression

The data compression is the process of reducing the space complexity of signals without loosing the information. When the data is compressed there are chances that the signals are disrupted and loss would occur. The wavelet transform is one of the major signal processing techniques that could be used to perform compression.

Applying the wavelet transform directly would compress the data but when restoring the information, there are higher chances of being introduced data loss. The lossless compression is highly recommended to perform any disease prediction. The ECG data should be compressed to maximum possible levels and also the restoration should occur efficiently without producing any error.

V. Data Compression Methods

There area number of data compression methods discussed for the problem of ECG data compression. This section discusses about the different methods for the problem of data compression. The compression methods can be classified into three different classes as follows:

A. Direct Method

Direct data compression of ECG signal for telemedicine [11], deals with efficient algorithms which have been developed after carrying out an exhaustive study of methods such as amplitude zone time epoch coding (AZTEC), modified AZTEC, Fan and scan along polygonal approximation (SAPA) techniques. In each of these techniques, modifications have been made to make it suitable for telemedicine purposes. Suitability of the system has been checked over transport control protocol (TCP), internet protocol (IP), local area network (LAN) and wide area network (WAN). The techniques have been tested for all standard leads of ECG signal of CSE database.

A comparison of different transform based methods for ECG data compression [12], a comparative study of Fast Fourier Transform (FFT), Discrete Cosine Transform (DCT) and Wavelet Transform (WT) transformations is carried.SLOPE-A real-time ECG data compressor [13], is presented. SLOPE considers some adjacent samples as a vector, and this vector is extended if the coming sample falls in a fan spanned by this vector and a theshold angle; otherwise, it is delimited as a linear segment. By this means SLOPE repeatedly delimits linear segments of different lengths and different slopes. The Huffman codes for the parameters to describe this linear segment are transmitted for that linear segment. SLOPEa which is a slightly modified version of SLOPE, is used to compress ambulatory ECG data.

SAPA-2is the Fan [14], presented recently as a method for representing electrocardiographic wavefoms as a series of straight-line segments, appears to be equivalent to an older algorithm, the Fan.Arrhythmia detection program for an ambulatory ECG monitor [15], a compression algorithm reduces the number of saved data points to one-half. After approximately 25 seconds of initialization, the software begins its search for the programmed arrhythmias. When the hardware R-wave detector finds an R wave, the program compares the time interval to the last R wave (R-R interval) both to previous R-R intervals. Thus, it senses a possible change in rhythm. When the program encounters an arrhythmia it signals an audible alarm. By checking a liquid crystal display, the patient can determine which condition initiated the alarm.

A real-time ECG data compression and transmission algorithm for an e health device [16], introduces a real-time data compression and transmission algorithm between e-health terminals for a periodic ECGsignal. The proposed algorithm consists of five compression procedures and four reconstruction procedures. In order to evaluate the performance of the proposed algorithm, the algorithm was applied to all 48 recordings of MIT-BIH arrhythmia database, and the compress ratio (CR), percent root mean square difference (PRD), percent root mean square difference normalized (PRDN), rms, SNR, and quality score (QS) values were obtained.

Ectopic beats in approximate entropy and sample entropy-based HRV assessment [17], Approximate entropy (ApEn) and sample entropy (SampEn) are the promising techniques for extracting complex characteristics of cardiovascular variability. Ectopic beats, originating from other than the normal site, are the artefacts contributing a serious limitation to heart rate variability (HRV) analysis. The approaches like deletion and interpolation are currently in use to eliminate the bias produced by ectopic beats. In this study, normal R–R interval time series of 10 healthy and 10 acute myocardial infarction (AMI) patients were analysed by inserting artificial ectopic beats.

Electrocardiogram compression technique for global system of mobile-based offline telecardiology application for rural clinics in India [18], describes an offline compression technique, which is implemented for ECG transmission in a global system of mobile (GSM) network for preliminary level evaluation of patient's cardiac condition in a non-critical condition. A short-duration (5-6 beats) ECG data from Massachusetts Institute of Technology-Beth Israel Hospital (MIT-BIH) arrhythmia database is used for the trial. The compression algorithm is based on direct processing of ECG samples in four major steps: viz., down-sampling of dataset, normalising inter-sample differences, grouping for sign and magnitude encoding, zero element compression and finally, conversion of bytes into corresponding 8 bit American standard code for information interchange (ASCII) characters.

A real-time ECG data compression and transmission algorithm for an e-health device [19], introduces a real-time data compression and transmission algorithm between e-health terminals for a periodic ECGsignal. The proposed algorithm consists of five compression procedures and four reconstruction procedures.A lossless ECG data compression technique using ASCII character encoding [20], A software based lossless ECG compression algorithm is developed here. The algorithm is written in the C-platform. The algorithm is applied to various ECG data of all the 12 leads taken from PTB diagnostic ECG database (PTB-DB). Here, a difference array has been generated from the corresponding input ECG data and this is multiplied by a large number to convert the number of arrays into integers. Then those integers are grouped in both forward and reverse direction, out of which a few are treated differently. Grouping has been done in such a way that every grouped number resides under valid ASCII value. Then all the grouped numbers along with sign bit and other necessary information are converted into their corresponding ASCII characters. The reconstruction algorithm has also been developed in using the reversed logic and it has been observed that data is reconstructed with almost negligible difference as compared with the original (PRD 0.023%).

Denoising and decorrelation of noisy and useful ECG components or signals signal-to-noise ratio is improved (ALSHAMALI, 2010), this paper proposes a new wavelet-based ECG compression technique[21]. Optimized thresholds determine thesignificant wavelet coefficients and an efficient coding for their positions. Huffman encoding is used to enhance the compression ratio.

Compressed sensing for real-time energy-efficient ECG compression on wireless body sensor nodes [22], quantify the potential of the emerging compressed sensing (CS) signal acquisition/compression paradigm for low-complexity energy-efficient ECG compression on the state-of-the-art Shimmer WBSN mote. Interestingly, our results show that CS represents a competitive alternative to state-of-the-art digital wavelet transform (DWT)-based ECG compression solutions in the context of WBSN-based ECG monitoring systems.

ECG signal compression using ASCII character encoding and transmission via SMS [23], Software based efficient and reliable ECG data compression and transmission scheme is proposed here. The algorithm has been applied to various ECG data of all the 12 leads taken from PTB diagnostic ECG database (PTB-DB). First of all, R-peaks are detected by differentiation and squaring technique and QRS regions are located. To achieve a strict lossless compression in the QRS regions and a tolerable lossy compression in rest of the signal, two different compression algorithms have used. The whole compression scheme is such that the compressed file contains only ASCII characters. These characters are transmitted using internet based Short Message Service (SMS) and at the receiving end, original ECG signal is brought back using just the reverse logic of compression.

DPCM quantizer adaptation method for efficient ECG signal compression [24], addresses the problem of electrocardiogram (ECG) signal compression with the goal to provide a simple compression method that outperforms previously proposed methods. Starting with the study of the ECG signal nature, the manner has been found to optimize rate-quality ratio of the ECG signal by means of differential pulse code modulation (DPCM) and subframe after subframe procession. Particularly, the proposed method includes two kinds of adaptations, short-time and long-time adaptations. The switched quantization i.e. the short-time DPCM quantizer range adaptation is performed according to the statistics of the ECG signal within particular subframes. It is ascertained that the short-time adaptation enables a sophisticated compression control as well as a constant quality of the ECG signal in both segments of low amplitude and high amplitude dynamics.

Compression of the ECG by prediction or interpolation and entropy encoding, [25], Compression of digital electrocardiogram (ECG) signals is desirable for two reasons: economic use of storage space for data bases and reduction of the data transmission rate for compatibility with telephone lines. In a sample of 220 4 lead ECG's the removal of signal redundancy by second-order prediction or interpolation with subsequent entropy encoding of the respective residual errors was investigated. At the sampling rate of 200 Hz, interpolation provided a 6 dB smaller residual error variance than prediction. A near-optimal value for the interpolation coefficients is 0.5, permitting simple implementation of the algorithm and requiring a word length for arithmetic processing of only 2 bits in extent of the signal precision. For linear prediction, the effects of occasional transmission errors decay exponentially, whereas for interpolation they do not, necessitating error control in certain applications.

Applications of Empirical Mode Decomposition for processing Nonstationary signals [26], a fully data-driven technique aimed at decomposing nonstationary signals in a set of “Intrinsic mode functions” (IMFs, Empirical modes). We will report on the main theoretical aspects of EMD, its extensive possibilities, and various contemporary applications. We will pay attention to detrending; denoising; Hilbert-Huang time-frequency analysis; and a very perspective and actual scientific direction known as Data Mining, which involves such problems as segmentation, cluster-analysis (clustering), classification, etc.

ECG data compression techniques—a unified approach [27], the theoretical bases behind the direct ECG data compression schemes are presented and classified into three categories: tolerance-comparison compression, DPCM, and entropy coding methods. A framework for evaluation and comparison of ECG compression schemes is presented.

Analysis and Design of On-sensor ECG Processors for Realtime Detection of Cardiac Anomalies Including VF, VT, and PVC [28], on-sensor ECG processors are designed for the realtime heart monitoring and analyzing SoC to give a timely warning against the fatal vascular signs. The system consists of an ASP to accelerate the CPSD algorithm as well as a GPP to control the system and provide better flexibility. Different architectures are discussed and compared, which leads to the conclusion that processing on the sensor node can reduce 98% power of wireless transmission for the raw ECG signals.

In Mean-shape vector quantizer for ECG signal compression [29], the mean values for short ECG signal segments are quantized as scalars and compression of the single-lead ECG by average beat subtraction and residual differencing their waveshapes coded through a vector quantizer. An entropy encoder is applied to both, mean and vector codes, to further increase compression without degrading the quality of the reconstructed signals. In this paper, the fundamentals of MSVQ are discussed, along with various parameters specifications such as duration of signal segments, the wordlength of the mean-value quantization and the size of the vector codebook. The method is assessed through percent-residual-difference measures on reconstructed signals, whereas its computational complexity is analyzed considering its real-time implementation.

A comparative analysis of independent component analysis (ICA) and PCA for correction of ECG signals is carried out by removing noise and artifacts from various raw ECG data sets[30]. PCA and ICA scatter plots of various chest and augmented ECG leads and their combinations are plotted to examine the varying orientations of the heart signal.ECG compression using long-term Prediction [31], new algorithm for ECG signal compression is introduced. The compression system is based on the subautoregression (SAR) model, known also as the long-term prediction (LTP) model. The periodicity of the ECG signal is employed in order to further reduce redundancy, thus yielding high compression ratios.

Design and Analysis for Compression of ECG Signal [32], examines lossless data compression algorithms and compares their performance. A set of selected algorithms are examined and implemented to evaluate the performance in compressing text data. The paper is concluded by stating which algorithm performs well for ECG Signal.ECG Data Compression Techniques – A Unified Approach [33], theoretical bases behind the direct ECG data compression schemes are presented and classified into three categories: tolerance-comparison compression, DPCM, and entropy coding methods. A framework for evaluation and comparison of ECG compression schemes is presented.

B. Transform Method

Transform method, converts the time domain signal to the frequency or other domains and analyzes the energy distribution. These methods mainly utilize the spectral and energy distributions of the signal by means of some transform, and properly encoding the transformed output. Signal reconstruction is achieved by an inverse transformation process. This category includes different transform techniques such as the Karhunen–Loève transform, Fourier transform, Cosine transform, sub-band-techniques, vector quantization (VQ), and more recently the wavelet transform. Wavelet technique is the obvious choice for ECG signal compression because of its localized and non-stationary property and the well-proven ability of wavelets to see through signals at different resolutions. The main task in wavelet analysis (decomposition and reconstruction) is to find a good analyzing function (mother wavelet) to perform an optimal decomposition [34].

An excellent wide range of data compression techniques based on various transformation techniques like DCT, FFT, DST and DCT2 were evaluated[35], to find an optimal compression strategy for ECG data compression. Wavelet compression methods were found to be suitable in terms of compression.

Wavelet based ECG data compression based on adaptive thresholding and efficient coding [36], proposes a new wavelet-based ECG data compression technique. It is based on optimized thresholds to determine significant wavelet coefficients and an efficient coding for their positions. The proposed technique is tested using several records taken from the MIT-BIH arrhythmia database. Simulation results show that the proposed technique outperforms others obtained by previously published schemes.

ECG compression using wavelet transform and particle swarm optimization [37],a new adaptive thresholding mechanism to determine the significant wavelet coefficients of an electrocardiogram signal, is proposed. It is based on estimating thresholds for different sub-bands using the concept of energy packing efficiency. Then thresholds are optimized using the particle swarm optimization algorithm to achieve a target compression ratio with minimum distortion. Simulation results on several records taken from the MIT-BIH Arrhythmia database show that the PSO converges exactly to the target compression after four iterations while the cost function achieved its minimum value after six iterations. Compared to previously published schemes, lower distortions are achieved for the same compression ratios.

Orthonormal bases of compactly supported wavelets [38], construct orthonormal bases of compactly supported wavelets, with arbitrarily high regularity. The order of regularity increases linearly with the support width. We start by reviewing the concept of multiresolution analysis as well as several algorithms in vision decomposition and reconstruction. The construction then follows from a synthesis of these different approaches.

Wavelet Transform

Wavelet transform is the method of reducing the signals to multi levels. By using the wavelet coefficient, the wavelet transform can be applied to compress the data.

Wavelet-based ECG data compression optimization with genetic algorithm [39], With a direct impact on compression performance, optimal quantization scheme is crucial for transform-based ECG data compression. However, traditional optimization schemes derived with signal adaption are commonly inherent with signal dependency and unsuitable for real-time application. In this paper, the variety of arrhythmia ECG signal is utilized for optimizing the quantization scheme of wavelet-based ECG data compression based on genetic algorithm (GA). The GA search can induce a stationary relationship among the quantization scales of multi-resolution levels. The stationary property facilitates the control of multi-level quantization scales with a single variable. For this aim, a three-dimensional (3-D) curve fitting technique is applied for deriving a quantization scheme with linear distortion characteristic. The linear distortion property can be almost independent of ECG signals and provide fast error control. The compression performance and convergence speed of reconstruction quality maintenance are also evaluated by using the MIT-BIH arrhythmia database.

ECG data compression using wavelet transform [40], ECG data compression has been one of the active research areas in biomedical engineering. In this paper a compression method for electrocardiogram (ECG) signals using wavelet transform is proposed. Wavelet transform compacts the energy of signal in fewer samples and has a good localization property in time and frequency domain. The MIT-BIH ECG signals are decomposed using discrete wavelet transform (DWT).The DWT provides powerful capability to remove frequency components at specific time in the data. The thresholding of the resulted DWT coefficients are done in a manner such that a predefined goal percent root mean square difference (GPRD) is achieved. The compression is achieved by the quantization technique, run-length encoding, Huffman and binary encoding methods. The proposed method, for fixed GPRD shows better performance with high compression ratios and good quality reconstructed signals.

The data compression technique for ECG signals using the singular value decomposition combined with discrete wavelet transform [41].The central idea is to transform the ECG signal to a rectangular matrix, compute the SVD, and then discard small singular values of the matrix. The resulting compressed matrix is wavelet transformed, threshold and coded to increase the compression ratio.An adaptive threshold mechanism to determine the significant wavelet coefficients of an electrocardiogram signal is proposed. It is based on estimating thresholds for different sub-bands using the concept of energy packing efficiency. Then thresholds are optimized using the particle swarm optimization algorithm to achieve a target compression ratio with minimum distortion.

ECG compression using slantlet and lifting wavelet transform with and without normalisation. [42], analyses the performance of: (i) linear transform: Slantlet transform (SLT), (ii) nonlinear transform: lifting wavelet transform (LWT) and (iii) nonlinear transform (LWT) with normalisation for electrocardiogram (ECG) compression. First, an ECG signal is transformed using linear transform and nonlinear transform. The transformed coefficients (TC) are then thresholded using bisection algorithm in order to match the predefined user-specified percentage root mean square difference (UPRD) within the tolerance. Then, the binary look up table is made to store the position map for zero and nonzero coefficients (NZCs). The NZCs are quantised by Max–Lloyd quantiser followed by Arithmetic coding. The look up table is encoded by Huffman coding.

A new algorithm for the compression of ECG signals based on mother wavelet parameterization and best-threshold levels selection [43], presents an ECG compression algorithm based on the optimal selection of wavelet filters and threshold levels in different subbands that achieve maximum data volume reduction while guaranteeing reconstruction quality. The proposed algorithm starts by segmenting the ECG signal into frames; where each frame is decomposed into subbands through optimized wavelet filters. The resulting wavelet coefficients are thresholded and those having absolute values below specified threshold levels in all subbands are deleted and the remaining coefficients are appropriately encoded with a modified version of the run-length coding scheme. The threshold levels to use, before encoding, are adjusted in an optimum manner, until predefined compression ratio and signal quality are achieved.

ECG PVC Classification Algorithm based on Fusion SVM and Wavelet Transform [44], proposes the electrocardiogram PVC classification algorithm based on support vector machine (SVM) and wavelet algorithm. The algorithm uses the wavelet transform to analyze ECG beating model, which is not influenced by the change of ECG waveform. The two feature sets respectively compose of statistical parameters of the wavelet coefficients and the selected wavelet coefficients. PVC and NSR are analyzed by using SVM.

Heart Rate and Ischemia Detection Using Wavelet Transform [45], An efficient method is implemented towards the detection of heart rate (HR) and ischemic from the ECG signal. The heart rate is calculated using the extracted features of the ECG signal for diagnosing cardiac arrest. The detection of ischemia from a patient's electrocardiogram (ECG) signal is based on the characteristics of a specific part of the beat called the ST segment which is used to diagnose the heart arrest. Wavelet transforms provides a good learning and detection capabilities which is an efficient tool to deal with uncertainties. Neural network classifier is used for classifying the abnormalities such as arrhythmia, types of ischemia as transmural and non transmural ischemia.

A novel compression algorithm for electrocardiogram signals based on the linear prediction of the wavelet coefficients [46], describes a new algorithm for electrocardiogram (ECG) compression. The main goal of the algorithm is to reduce the bit rate while keeping the reconstructed signal distortion at a clinically acceptable level. It is based on the compression of the linearly predicted residuals of the wavelet coefficients of the signal. In this algorithm, the input signal is divided into blocks and each block goes through a discrete wavelet transform; then the resulting wavelet coefficients are linearly predicted. In this way, a set of uncorrelated transform domain signals is obtained. These signals are compressed using various coding methods, including modified run-length and Huffman coding techniques. The error corresponding to the difference between the wavelet coefficients and the predicted coefficients is minimized in order to get the best predictor.

ECG Data Compression Using DWT [47], compression method for electrocardiogram (ECG) signals using wavelet transform is proposed. Wavelet transform compacts the energy of signal in a fewer samples and has a good localization property in time and frequency domain. The MIT-BIH ECG signals are decomposed using discrete wavelet transform (DWT).The DWT provides powerful capability to remove frequency components at specific time in the data. The thresholding of the resulted DWT coefficients are done in a manner such that a predefined goal percent root mean square difference (GPRD) is achieved.

A new hybrid two-stage electrocardiogram (ECG) signal compression method based on the modified discrete cosine transform and discrete wavelet transform is proposed. The ECG signal is partitioned into blocks and the MDCT is applied to each block to decorrelate the spectral information. Then, the DWT is applied to the resulting MDCT coefficients. Removing spectral redundancy is achieved by compressing the subordinate components more than the dominant components. The resulting wavelet coefficients are then thresholded and compressed using energy packing and binary-significant map coding technique for storage space saving[48].

A hybrid ECG compression algorithm based on SVD and discretewavelet transform [49], presents a compression technique for ECG signals using the singular value decomposition (SVD) combined with discrete wavelet transform (DWT). The central idea is to transform the ECG signal to a rectangular matrix, compute the SVD, and then discard small singular values of the matrix. The resulting compressed matrix is wavelet transformed, thresholded and coded to increase the compression ratio. The number of singular values and the threshold level adopted are based on the percentage root mean square difference (PRD) and the compression ratio required.

A Multiscale Wavelet Transformation and Amplitude Zone Time Epoch Coding technique is used fprefficient ECG data compression process [51]. This mechanism will decompose the ECG signals into many sub-bands and to extract the P, T waves and QRS complex. After extraction of signals, Amplitude Zone Time Epoch encoding and decoding Techniques are introduced for data compression and decompression. This in turn helps to improve the data extraction and data compression performance in IMGWT–AZTEC mechanism.

A survival study is taken for feature extraction and compression of ECG signal [52]. The efficiency of data extraction and compression technique is tested with the metrics such as Feature extraction accuracy, Compression

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Ratio and Space ComplexityWith the simulations conducted for Discrete Wavelet Transform (DWT) and SVD-ASWDR technique, it is observed that improves the feature extraction accuracy and compression ratio respectively.

C. Fast Fourier Transfrom Method

The fast fourier transform method seperates the components of ECG waveform. For each component the method computes the frequency and time between two different samples. Then the FFT coefficients are identified and count the samples. Then the method computes the inverse Fourier transform. Then the compression ratio is computed.

D. Discrete Cosine Transform Method:

TABLE I
DETAILS OF EVALUATION PARAMETERS

Parameter	Compression Ratio
Dataset Name	PhysioNet
Number of classes	9
Number of samples	262

In discrete cosine transform method, the ECG data is read and its components are extracted. Then the frequency of each component and time are computed. Then DCT of ECG waveform is computed and validated with the DCT coefficients.

An improvement of a discrete cosine transform (DCT)-based method [50] for electrocardiogram (ECG) compression is presented. The appropriate use of a block based DCT associated to a uniform scalar dead zone quantizes and arithmetic coding shows very good results. Improved ECG compression method usses discrete cosine transform. An improvement of a discrete cosine transform (DCT)-based method for electrocardiogram (ECG) compression is presented. The appropriate use of a block based DCT associated with a uniform scalar dead zone quantiser and arithmetic coding shows very good results, confirming that the proposed strategy exhibits competitive performances compared with most popular compressors used for ECG compression.

E. .Discrete Sine Transform Method:

Discrete sine transform (DST) is a Fourier-related transform similar to the discrete Fourier transform (DFT), but using a purely real matrix. It is equivalentto the imaginary parts of a DFT of roughlytwice the length, operating on real data with odd symmetry (since the Fourier transform of a real and odd function is imaginary and odd), where in some variants the input and/or output data are shifted by half a sample. Like any Fourier-related transform, discrete sine transforms (DSTs) express a function or a signal in terms of a sum of sinusoids with different frequencies and amplitudes.

VI. MULTI VARIANCE MATRIX BASED DATA COMPRESSION

The problem of data compression can be approached using the multi variance matrix approach. In this method the features of the ECG waveform can be extracted. From the extracted features, the method computes the time and amplitude values. Based on computed time and amplitude values, the method computes the variance value. Computed variance value with the base value is stored to the variance matrix. This reduces the data storage required for the ECG waveform data. The compression process involves the following stages:

TABLE II
COMPARATIVE RESULT ON VARIOUS PARAMETERS

Method Name	COMPRESSION RATIO	PRD
MDCT	90.43	0.9382
Adaptive Threshold	85.18	1.2589
PVC	87.20	1.267
FFT	89.57	1.661
SAPA	88.67	1.483
SAPA-2	89.13	1.324
DPCM	90.30	1.768
WT-PSO	91.26	1.890

A. Preprocessing

The wavelet filter is used to preprocess the input waveform signals. The signals with poor amplitude are identified and hiked to next level and the signals less than minimum amplitude are ignored as noise. The noise removed signals are used for feature extraction.

B. Feature Extraction

In this stage, the method extracts the PQRST components and splits the P-QRS-T waves separately. From the separated components the method computes the time and frequency values. Extracted features are stored with the feature vector.

C. Multi Feature Variance Matrix Generation and Data Compression

In this stage, the method computes the variance of measures in time and amplitude. For each signal and wave component, the method computes the variance measure. Computed variance value is stored with base value in the variance matrix.

VII. RESULTS AND DISCUSSION

The algorithms discussed in this paper have been evaluated for their efficiency with the ECG dataset. The details of implementation has been presented in the table below:

The Table1, shows the details of data set being used for the performance evaluation of different methods. The performance of the compression method can be measured by computing the compression ratio (CR) and Error Rate.

Compression Ratio (CR)

CR is the ratio of the original data to compressed data without taking into account factors such as bandwidth, sampling frequency, precision of the original data, word-length of compression parameters, reconstruction error threshold, database size, lead selection, and noise level. It is given by:

CR = Bit rate of original file / Bit rate of reconstructed file ……………… (1)

That is, the Higher the CR,the smaller the size of the compressed file.

Percentage Mean Square Difference (PRD):

Percentage Mean Square Difference (PRD) is a measure of error loss. This measure evaluates the distortion between the original and the reconstructed signal. PRD calculation is as follows:

$$PRD = \sqrt{\Sigma (Xi - Xi1)2 / \Sigma Xi2} \quad \ldots\ldots\ldots\ldots \quad (2)$$

where Xi is the original file and Xi1 is its reconstructed version.

The ECG data is sampled at 333 Hz. The amount of compression is measured by CR and the distortion between the original and reconstructedsignal is measured by PRD. The comparison shown in Table 2, details the results of compression techniques. This gives the choice to selectthe best suitable compression method. A data compression algorithm must represent the data with acceptable fidelity while achieving high CR. The PRD indicates reconstruction fidelity and the increase in its value is actually undesirable. Although DCT-II provides maximum CR, the distortion is more. Therefore,a compromise is made between CR and PRD.

Table 2 gives the result of various parameters of data compression achieved by different methods. It clearly shows that the proposed method has produced higher compression ratio.

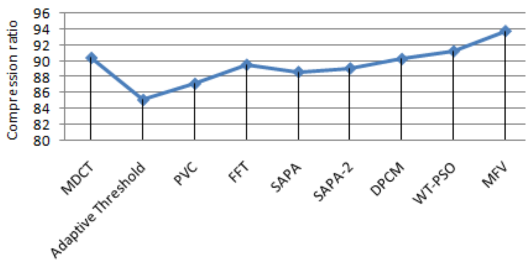

Fig. 2. Comparison of compression ratio

Fig2 shows the comparison of compression ratio achieved by different methods and the result shows that the proposed multi feature variance method has produced efficient results in data compression.

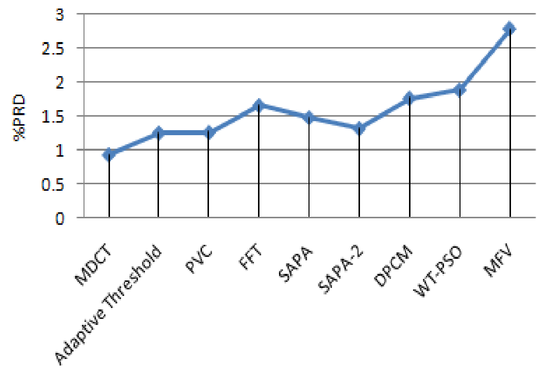

Fig. 3. Comparison of mean square difference produced

Fig3 shows the comparison of mean square difference produced by different methods and it shows clearly that the proposed method has produced efficient result in PSD.

VIII. CONCLUSIONS

This paper performs a detailed review of various methods described for ECG data compression. Each method has been verified for their efficiency in data compression using standard data set. Further multi feature variance matrix (MFV) based data compression technique has been presented. The MFV method produces data compression ratio upto 94 %.

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