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Adaptive Detection and Classification of Life Threatening Arrhythmias in ECG Signals Using Neuro SVM

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Abstract—*Electrocardiogram is a method of measuring the electrical activities of heart. Every portion of ECG is very essential for the diagnosis of different cardiac problems. But the amplitude and duration of ECG signal is usually corrupted by different noises. Here a broader study for denoising every types of noise involved with real ECG signal is done. Different types of adaptive filters are considered to reduce the ECG signal Base Line Interference. Hence adaptive filters, now a day, are used for artefact removal from ECG signals. Adaptive filters update their coefficients according to the requirement. There are various adaptive algorithms such as Least Mean Square (LMS), Recursive Least Square (RLS), Normalized Least Mean Square (NLMS) etc are present. Moreover, there is one more method is described which is patch based and used for artifact rejection from ECG signals. This method was previously used only for image denoising but now it has been using for artefact rejection from biomedical signals.Here, Least Mean Square (LMS) algorithm and patch based method has been implemented for denoising the ECG signal.*

Keywords—Electrocardiogram, LMS, RLS, NLMS, Denoising, Adaptive filters, Signal Processing.

I. INTRODUCTION

ElectroCardioGraphy(ECG) records the electrical activity of the heart. It can be detected by several electrodes attached to the different positions of the body and recorded by using an external electronic device. It is used as a test to gather information about different heart diseases. A typical ECG signal consists of a P-wave, a QRS complex and a T-wave as shown in fig 1.

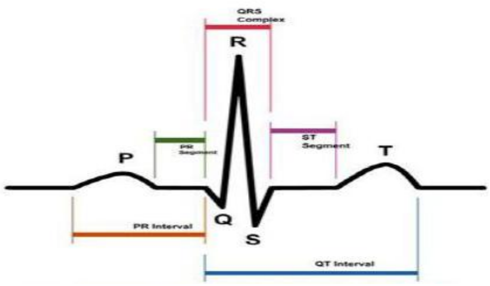

FIG.1 STANDARD NOISE FREE ECG SIGNAL

The LMS algorithm is extensively used in different application of adaptive filtering due to low computational complexity, stability and unbiased convergence. Compression methods have gained in importance in recent years in many medical areas like telemedicine, health monitoring, etc. All these imply storage, processing, and transmission of large quantities of data. Compression methods can be classified into two main categories: lossless and lossy. Compression algorithms can be constructed through direct methods, linear transformations, and parametric methods.

II. METHODS USED

When the doctors are examining the patient on-line and want to review the ECG of the patient in real-time, there is a good chance that the ECG signal has been contaminated by noise. The predominant artifacts present in the ECG includes: Power-line Interference (PLI), Baseline wander (BW), Muscle Artifacts (MA) mainly caused by patient breathing, movement, power line interference, bad electrodes and improper electrode site preparation. The low frequency ST segments of ECG

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signals are strongly affected by these contaminations, which lead to false diagnosis. To allow doctors to view the best signal that can be obtained, we need to develop an adaptive filter to remove the noise in order to better obtain and interpret the ECG data.

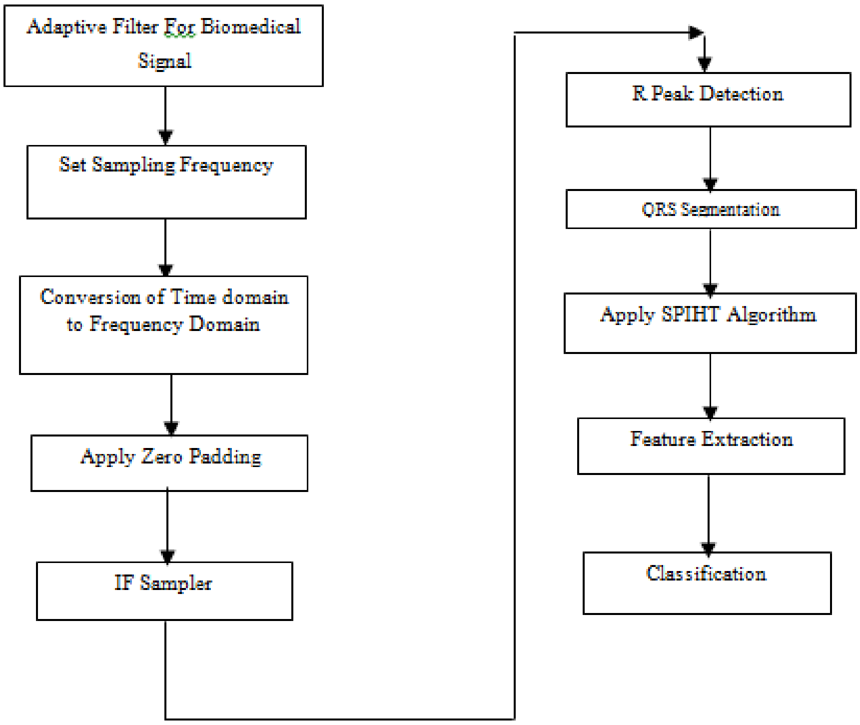

FIG 2 FLOW DIAGRAM OF PROPOSED SYSTEM

The acquisition data stage has a hardware part composed by the A/D converter, and a software part which is in charge of directing the A/D converter work. Any programming language allowing low level hardware instruction is usable.C and Visual Basic programming languages are used for getting and processing the ECG signal. According to these works, the routine written in C language is used to direct the A/D converter functioning using non-standard functions to access the personal computer ports.

The obtained quantity of samples is stored in a binary file which is rescued by the Visual Basic programming language routine to processing (applying filters and QRS detection algorithms) and showing the signal. Showing the signal at the computer is done “offline” from the generated file with the ECG signal samples. As highlights using current high level programming languages would be possible to build a showing graphics routine. Using lineal interpolation it is possible to get high level graphic results.

Even though the Nyquist’s sample theorem indicates that a signal can be rebuild using an ideal interpolation method by means of lineal interpolation, and through this it is possible to get good results for low frequency signals like ECG. It is possible to build a universal graphics generator for getting signal. These signals are low frequency signals (2 Hz) generated by a function or electrical wave’s generator with some acquisition deformities (high negative values are not considered).

Initially a reference signal is taken and denoised followed by compression and storage of the signal by using SPIHT algorithm shown in fig 2. Then the features of the compressed signal are extracted and classified using neuro SVM.

III. ADAPTIVE FILTERS

Figure shows an adaptive filter with a primary input that is an ECG signal *s1* with additive noise *n1*. While the reference input is noise *n2*, possibly recorded from another generator of noise *n2* that is correlated in some way with *n1*.

If the filter output is y and the filter error $e= (s1+n1)-y$, then

$$(e)^2 = (s1 + n1)^2 - 2\mathrm{y}(\mathrm{s1} + \mathrm{n1}) + (y)^2 \tag{1}$$
$$= (n1 - y)^2 + (s1)^2 + 2\mathrm{s1n1} - 2\mathrm{ys1}$$

Since the signal and noise are uncorrelated, the mean-squared error (MSE) is

$$\mathrm{E}(e)^2 = \mathrm{E}[(n1 - y)^2] + \mathrm{E}(\mathrm{s1})^2 \tag{2}$$

Minimizing the MSE results in a filter error output that is the best least-squares estimate of the signal $s1$. The adaptive filter extracts the signal, or eliminates the noise, by iteratively minimizing the MSE between the primary and the reference inputs shown in fig 3.

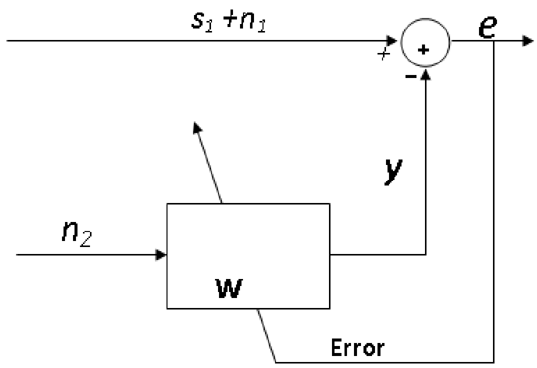

FIG 3: FILTER STRUCTURE

Due to simplification of gradient vector computation, LMS is used. The overview of the structure and operation of the LMS algorithm can be discussed according to LMS algorithm's properties and its processes. The convergence behavior in a stationary environment of LMS algorithm is its main feature. LMS is a linear adaptive filtering algorithm and is consists of two basic processes. First one is filtering process, which involves computing the output y(n) of linear filter in response to an input signal x(n), generating an estimation error e(n) by comparing this output y(n) with desired response d(n).Second one is an adaptive process, which involves the automatic adjustment of the parameters of the filter in accordance with the estimation error e(n).

LMS filter working is based on finding the filter coefficients that leads to minimizing the mean square of the error which is the difference between the desired signal and error signal. In order for LMS filter to approach the optimum filter weights, the algorithm starts by assuming small weights (zero) and at each step, it finds the gradient of the mean square error and then updates the weights.

If the mean square error is positive, error is increases positively and if same error is used, filters weights needs to be reduced accordingly. And vice versa, if gradient is negative, filter weights need to be increased. Weight update equation is as below,

$$\mathrm{W(i)} = \mathrm{w(i\text{-}1)} + \mu\, \mathrm{e(i)}\, \mathrm{x(i)} \tag{3}$$

Where (i), x(i), μ and w(i) are the error, the input, step size parameter and the weight function respectively. If the step size parameter μ is significantly small, LMS algorithm converges in the mean square provided that u satisfies the condition given below,

$$0 < \mathrm{u} < (1 / \lambda\mathrm{max})$$

Where, λm axis the largest eigen value of the correlation matrix.

The LMS algorithm is summarized as below:

(i) Inputs

x = input signal
dn = desired signal
M = Filter Length
μ = Step-size factor

(ii) Outputs

y = output of filter
e = error signal

(iii) Pseudo-code

Initialize:
Filter coefficient w(1) = 0
Loop1:
For every i, do
Calculate e(i) = d(i) – w(i)T x(i)
Update w(i) = w(i) + μ e(i) x(i)
End

IV. SIGNAL COMPRESSION

An ElectroCardioGram (ECG) signal is compressed based on Discrete Wavelet Transform (DWT) and QRS-complex estimation. The ECG signal is preprocessed by normalization and mean removal. Then, an error signal is formed as the difference between the preprocessed ECG signal and the estimated QRS-complex waveform. This error signal is wavelet transformed and the resulting wavelet coefficients are threshold by setting to zero all coefficients that are smaller than certain threshold levels. The threshold levels of all sub-bands are calculated based on Energy Packing Efficiency (EPE) such that minimum Percentage Root mean square Difference (PRD) and maximum Compression Ratio (CR) are obtained. It is also a lossy compression technique but performs better than DCT. Wavelet Transform (WT) is a powerful time-frequency signal analysis tool and it is used in a wide variety of applications including signal and image coding. Discrete Wavelet transform has an orthogonal basis function and exhibits zero redundancy.

Transmission techniques of biomedical signals through communication channels are currently an important issue in many applications related to clinical practice. These techniques can allow experts to make a remote assessment of the information carried by the signals, in a very cost-effective way. However, in many situations this process leads to a large volume of information. The necessity of efficient data compression methods for biomedical signals is currently widely recognized. This chapter introduces the compression of ElectroCardioGram (ECG or EKG) signals using Discrete Wavelet Transform (DWT).

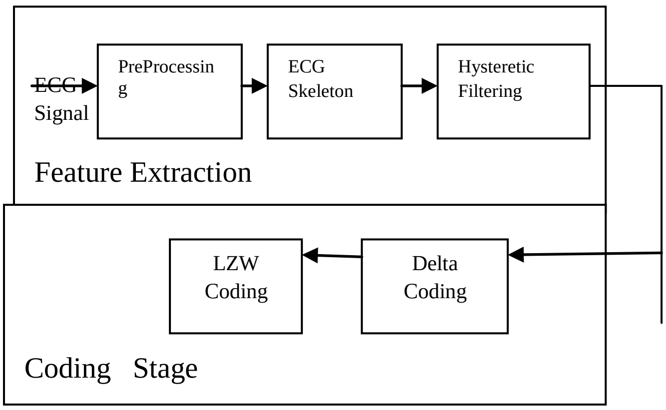

FIG 4: SCHEMATIC DIAGRAM FOR ECG SIGNAL COMPRESSION

It is well known that modern clinical systems require the storage, processing and transmission of large quantities of ECG signals. ECG signals are collected both over long periods of time and at high resolution. This creates substantial volumes of data for storage and transmission.

Data compression seeks to reduce the number of bits of information required to store or transmit digitized ECG signals without significant loss of signal quality shown in fig 4.Although storage space is currently relatively cheap, electronic ECG archives could easily become extremely large and expensive. Moreover, sending ECG recordings through mobile networks would benefit from low bandwidth demands. ECG signal compression attracted considerable attention over the last decade. Several examples of ECG compression algorithms have been described in the literature with compression ratios ranging approximately from 2:1 up to 50:1.

The main goal here is to provide an up-to-date introduction to this fascinating field; through presenting some of the latest algorithmic innovations and to stimulate readers to investigate the subject in greater depth using the extensive set of references provided. Data reduction of ECG signal is achieved by discarding digitized samples that are not important for subsequent pattern analysis and rhythm interpretation. The data reduction algorithms are empirically designed to achieve good reduction without causing significant distortion error. ECG compression techniques can be categorized into: direct time-domain techniques; transformed frequency-domain techniques and parameters optimization techniques.

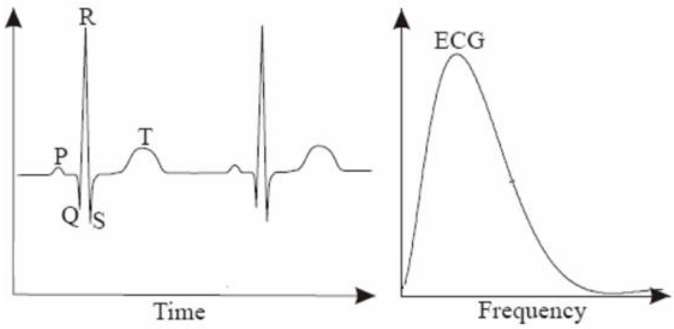

FIG 5 : ECG SIGNAL IN TIME AND FREQUENCY DOMAIN

These principles are partial ordering of transform coefficients by magnitude with a set partitioning sorting algorithm, ordered bit plane transmission and exploitation of self similarity across different scales of an image wavelet transform shown in fig 5. The partial ordering is done by comparing the transform coefficients magnitudes with a set of octavely decreasing thresholds. In this algorithm, a transmission priority is assigned to each coefficient to be transmitted. Using these rules, the encoder always transmits the most significant bit to the decoder. SPIHT algorithm is modified for 1-D signals and used for ECG compression. For faster computations SPIHT algorithm can be described as follows:

1. ECG signal is divided to contiguous non-overlapping frames each of N samples and each frame is encoded separately.
2. DWT is applied to the ECG frames up to L decomposition levels.
3. Each wavelet coefficient is represented by a fixed-point binary format, so it can be treated as an integer.
4. SPIHT algorithm is applied to these integers (produced from wavelet coefficients) for encoding them.
5. The termination of encoding algorithm is specified by a threshold value determined in advance; changing this threshold, gives different compression ratios.
6. The output of the algorithm is a bit stream (0 and 1). This bit stream is used for reconstructing signal after compression. From it and by going through inverse of SPIHT algorithm, we compute a vector of N wavelet coefficients and using inverse wavelet transform, we make the reconstructed N sample frame of ECG signal.

V. RESULTS

The ECG Signal denoising and compression is performed by using adaptive filter is simulated using MATLAB in windows 8 Operating Platform and the following results are obtained.

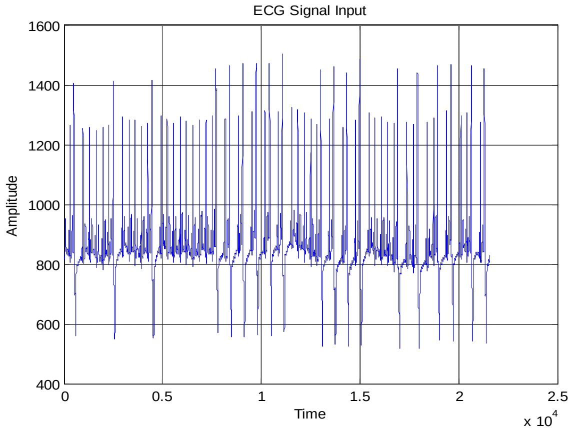

FIG 6: INPUT SIGNAL TO BE COMPRESSED

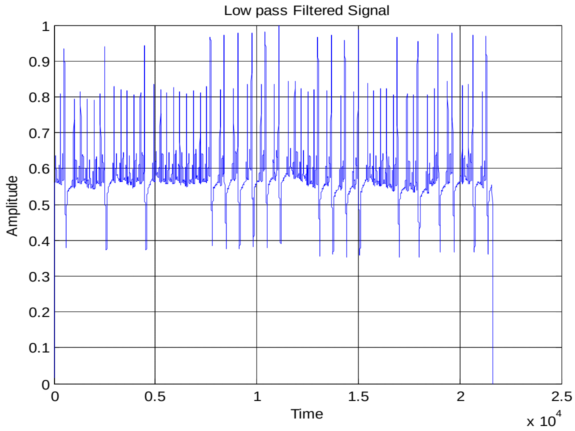

FIG7 ECG SIGNAL USING LOW PASS FILTER

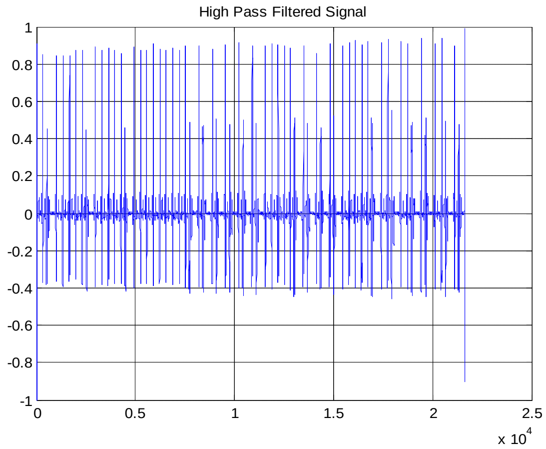

FIG 8.ECG SIGNAL AFTER HIGH PASS FILTER

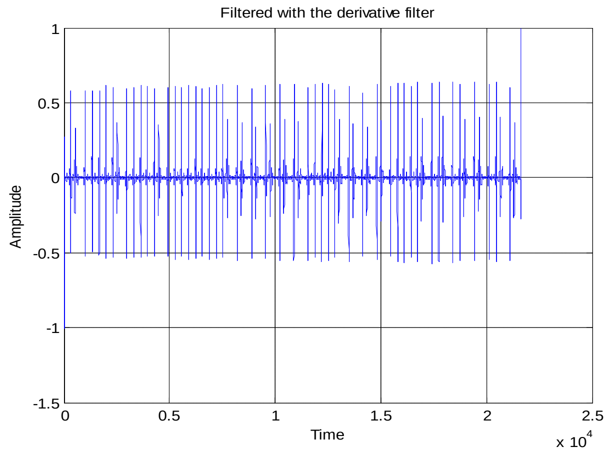

FIG 9: ECG SIGNAL AFTER DERIVATIVE FILTER

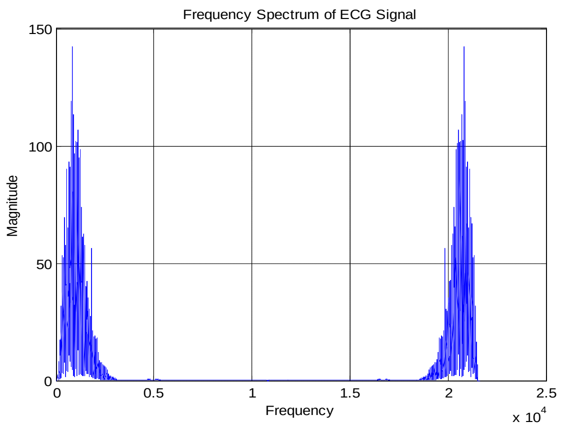

FIG 10:ECG SIGNAL SPECTRUM ESTIMATION USING FAST FOURIER TRANSFORM

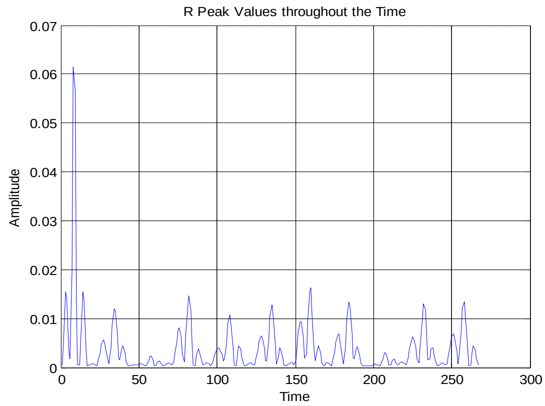

FIG 11: ECG SIGNAL R PEAK DETECTION

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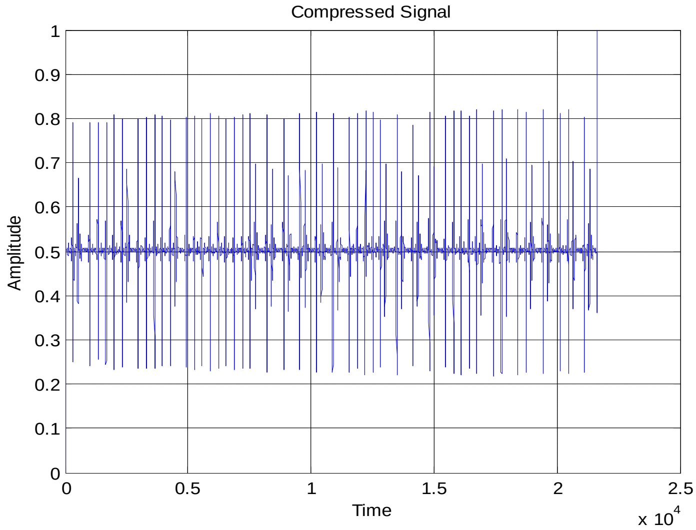

FIG 12: ECG SIGNAL COMPRESSION

VI. CONCLUSION

The proposed system analyses the compression of ECG signal based on SPIHT algorithm using wavelet transform. The R peak complex is estimated using parameters extracted from the original ECG signal. This method is applied to many ECG records selected from the MIT-BIH arrhythmia database. It Results in Compression Ratio higher than previously published results.

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