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ECG Signal Preprocessing and SVM Classifier-Based Abnormality Detection in Remote Healthcare Applications

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ABSTRACT Medical expert systems are part of the portable and smart healthcare monitoring devices used in day-to-day life. Arrhythmic beat classification is mainly used in electrocardiogram (ECG) abnormality detection for identifying heart related problems. In this paper, ECG signal preprocessing and support vector machine-based arrhythmic beat classification are performed to categorize into normal and abnormal subjects. In ECG signal preprocessing, a delayed error normalized LMS adaptive filter is used to achieve high speed and low latency design with less computational elements. Since the signal processing technique is developed for remote healthcare systems, white noise removal is mainly focused. Discrete wavelet transform is applied on the preprocessed signal for HRV feature extraction and machine learning techniques are used for performing arrhythmic beat classification. In this paper, SVM classifier and other popular classifiers have been used on noise removed feature extracted signal for beat classification. Results indicate that the performance of SVM classifier is better than other machine learning-based classifiers.

INDEX TERMS Adaptive filter, arrhythmic beat classification, ECG preprocessing, SVM classifier, machine learning.

I. INTRODUCTION

Heart related diseases and their diagnosis from electrocardiogram (ECG) has greater importance in medical applications. Each heartbeat in the cardiac cycle of the ECG waveform describes the time evolution of the heart's electrical activity, which is made of diverse electrical depolarization-repolarization. Any uncertainty of heart rate or rhythm, or variation in the morphological pattern, is an indication of an arrhythmia, which could be identified by the analysis of recorded ECG waveform [1]. Two widely known heart diseases reported in medical literature are myocardial ischaemia and cardiac arrhythmias. Myocardial ischaemia occurs due to the reduction in blood supply to myocardium which alters the morphology of ECG signal [2]. Cardiac arrhythmias indicate most of the cardiovascular problems that may lead to chest pain, cardiac arrest or sudden cardiac death [3]. Since arrhythmic beat classification provides several important data about cardiac condition of human beings, Electrocardiogram (ECG) based morphological analysis has been used in the past for the assessment of arrhythmias at the expense of more computational elements. Keeping in view of the ECG signal based analysis, wide spread attention has been paid over the years towards the study of variations in the beat-to-beat timing of the heart, referred to as heart rate variability (HRV) [4]. HRV is feature extracted from the ECG signal variations that is more powerful in identification of cardiac disorders and associated diseases [5].

The preprocessing of ECG signal is performed to remove the base line wander, motion artifacts and other interruptions of original recorded signal [6]. In telemedicine applications, transmission of ECG signals over a wireless channel is often affected by noises due to improper channel. The noises are normally modeled as white Gaussian noise. In some applications, white Gaussian noise is considered as a general frequency noise source and is added to the uncontaminated ECG signals. Many filtering and noise removal techniques have been adopted for the white noise removal [7]. A white Gaussian noise removal technique using Wiener filtering approach has been proposed in the literature. Wiener filter is an optimal filter and is especially useful when the power spectrums of input signal and noise overlap and are not separable by traditional low-pass filters. Adaptive filtering based noise removal is applied in this work for the obtained ECG data. Computational complexity is the major issue in adaptive filtering technique and its applications. Research advancement in very large scale integration (VLSI) technology leads to less cost and minimum number of elements [8].

Existing ECG noise removal techniques based on Wavelet, EMD and RLS based adaptive filtering require more computations than LMS based adaptive filtering. Hence, it is preferred to have a white Gaussian noise removal by LMS based adaptive filtering to reduce power consumption. However, in LMS based adaptive filtering, a large step size is required to achieve a better filtering performance. One of the primary disadvantages of the adaptive LMS algorithm is having a fixed step size parameter for every iteration which severely affects the filtering performance [9]. To improve the filtering performance, an LMS algorithm with normalized step size is suggested in many research works. In this work, a delayed error normalized LMS (DENLMS) adaptive filter is used for ECG noise removal with less computational complexity.

ECG signal noise removal is followed by feature extraction. In this stage, R-peaks of the denoised ECG are extracted using wavelet based methods for HRV analysis. Discrete wavelet transform (DWT) is widely popular for many information extraction techniques, but the mother wavelet selection is crucial in most of the feature extraction processes. Since the all wavelets are produced from mother wavelet through translation and scaling, mother wavelet needs to be carefully selected [10]. In wavelet transform, successive transformations are done on approximation coefficient to obtain the original signal at the cost of negligible amount of information. Wavelets and its performance are also decided based on the number of coefficients and level of decomposition. Coiflet wavelet is applied here for the HRV feature extraction from the ECG signal. The Coiflets are formed from Daubechies wavelet, but are more symmetric and has near linear phase and its characteristics are much better than Daubechies wavelet and Spline wavelet [11]. Discrete wavelet transform based R-peak detection technique is chosen in this paper to reduce the computational complexity. R-peak detection techniques are mainly based on heart rate function which is widely used to calculate the RR interval. Dividing one minute by the instantaneous heart rate gives the RR interval of the given ECG signal. Consecutive RR intervals of the ECG signal are calculated from starting interval of the heart rate function. Numerous wavelets have been utilized for R-peak (QRS complex) detection in ECG signals [12]. Among the various forms of wavelets, Coiflet is selected in this work as they give better results for QRS complex detection in ECG signals [13].

Machine learning techniques evolve from artificial intelligence concepts that can be used in computational tasks where the conventional algorithms are infeasible. Artificial neural networks are based on the biological neurons that are used to model complex relationship between inputs and outputs [14]. Rule base machine learning algorithms are widely adopted is the medical applications to create a medical expert system. K-Nearest-Neighbor (KNN) Rule is widely recognized as a sample classification technique in many applications [15], [16]. The Support Vector Machine (SVM) is widely used for classification of feature extracted ECG data compared to other machine learning techniques such as decision tree classifier, genetic algorithm and deep learning [17].

Frequency domain analysis of HRV provides vital information about cardiovascular control which is crucial in the identification of sympathetic and parasympathetic activities [18]. There are three important frequency regions in human HRV signal. They are very low frequency (VLF) which is below 0.04 Hz, low frequency (LF) that varies between 0.04 and 0.15 Hz and high frequency (HF) that is from 0.15 to 0.5 Hz is. While the LF spectrum is affected due to both sympathetic and parasympathetic activities, HF spectrum is largely found in parasympathetic activity [19]. The extracted frequency domain features and computed features of HRV are classified into normal and abnormal using SVM classifier.

In this work, ECG signal preprocessing is performed by DENLMS adaptive filter and HRV features are extracted using DWT. Arrhythmic beat classification is performed by SVM classifier and the performance is compared with similar classifiers. The paper is organized into five sections including the introductory section. ECG signal preprocessing using DENLMS algorithm is provided with convergence and stability analysis in section 2. DWT based feature extraction and abnormality detection using KNN Classifier are described in section 3. Section 4 discusses the obtained results and section 5 concludes the proposed work.

II. ECG SIGNAL PREPROCESSING AND FEATURE EXTRACTION

A. DENLMS ALGORITHM

The LMS algorithm is the most preferred choice in adaptive filters due to its computational simplicity. In each iteration of the standard LMS algorithm, the FIR filter coefficients are modified based on the following weight update equation

$$w(n+1) = w(n) + \mu x(n)e(n) \tag{1}$$

where n, $w(n)$ *and* $w(n+1)$ indicate time step, old weight and updated weight respectively. μ is the step size which is used to control the stability and convergence performance of the filter. $x(n)$ indicates the filter input and $e(n)$ is the error signal that decides the weight update of filter coefficients.

The adaptive filter output $y(n)$ is then calculated by updated weight and input in equation (2) as

$$y(n) = w^t(n)x(n) \tag{2}$$

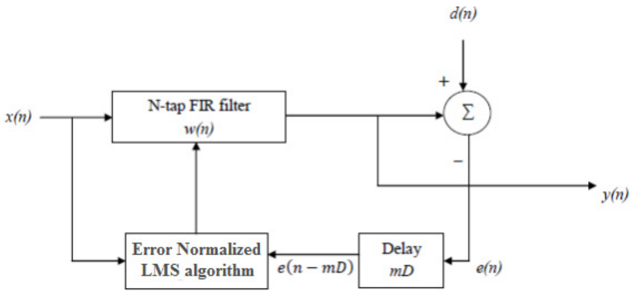


FIGURE 1. Block diagram of proposed DENLMS algorithm.

where $w^t(n)$ represents the filter weights that are associated with transposed matrix. The filter error output $e(n)$ is written based on the actual filter output and desired output

$$e(n) = d(n) - w^t(n)x(n) \tag{3}$$

In the modeling of adaptive LMS filter, the input ECG signal $x(n)$ is assumed to be corrupted with the additive noise $v(n)$. While MSE is minimized by applying adaptive algorithms, filter produces the best least-squares estimate of the signal $x(n)$. The MSE is expressed by the equation

$$E[e^2(n)] = E[(x(n) - y(n))^2] + E[v^2(n)] \tag{4}$$

Pipelining an adaptive filter is not a simple task because of the presence of feedback structure. It is important to ensure that the pipelined filter has to converge for the same number of coefficients used for the filter without pipelining.

Hence the pipelining ideas of impulse invariant response (IIR) filter can be used, because they have feedback structure. The LMS algorithms are very much popular in many adaptive filtering applications, because it requires $2N$ additions and $2N + 1$ multiplications [20].

Three main stages of delayed LMS algorithm are: i) Calculating updated weights ii) Finding the error signal iii) Estimation of output signal. Weight update, error calculation and output are given in equations (5), (6) and (7) respectively.

$$w(n + 1) = w(n) + \mu e(n - kD)x(n - kD) \tag{5}$$

where μ is the step size.

$$e(n - kD) = d(n - kD) - y(n - kD) \tag{6}$$

$$y(n - kD) = w^T(n - kD)x(n - kD) \tag{7}$$

Where kD indicates the number of delays used in the pipelining stage.

Figure 1 depicts the components of the proposed DENLMS algorithm. The constant step size decides the filter convergence rate and the steady-state behavior. The convergence of delayed LMS algorithm is described in the Equation (8), using filter order N, the pipelining stages k and the tap-input power (P_{TI}) [21].

$$0 < \mu < \frac{2}{(N - 2k - 2)(P_{TI})} \tag{8}$$

The NLMS algorithm can be written using coefficient update equation as

$$w(n + 1) = w(n) + \mu_n e(n)x(n) \tag{9}$$

Where μ_n is the normalized step size. The normalized step size can be expressed as

$$\mu_n = \left[\frac{\mu}{p + x^t(n)x(n)}\right] \tag{10}$$

where parameter p is set to avoid the small denominator value and big step size.

B. DWT BASED FEATURE EXTRACTION

In DWT based feature extraction, the R-peaks are detected to determine the HRV signal features. Arrhythmic beat classification is performed to detect abnormalities in ECG signal using SVM classifier. R-peak detection techniques are mainly based on heart rate function which is widely used to calculate the RR interval. Dividing one minute by the instantaneous heart rate gives the RR interval of the given ECG signal. Consecutive RR intervals of the ECG signal are calculated from starting interval of the heart rate function. Among the Meyer, Biorthogonal, reverse Biorthogonal and Coiflet wavelets, Coiflet is chosen to extract R-peaks. In practical RR interval measurement system, correlation technique with timing resolution ± 1 ms is used. The accurate RR interval measurement can be obtained by high performance digital signal processor or customized processor. Considerable amount of baseline trend in ECG signal is removed using the adaptive filtering based preprocessing.

III. ARRHYTHMIC BEAT CLASSIFICATION FOR ECG ABNORMALITY DETECTION

Time domain and frequency domain features can be derived from the extracted HRV features. Figure 2 depicts the components involved in the arrhythmic beat classification based on preprocessing and HRV feature extraction. The proposed ANFIS evaluation consists of i) Collection of raw electrocardiogram (ECG) signal from MIT-BIH database, ii) Preprocessing of ECG signal using adaptive filter iii) R-peak detection iv) Frequency domain feature extraction from HRV signal v) SVM classification into normal and abnormal.

There are 14 well known time domain and frequency domain HRV features. Time domain HRV parameters used are RR mean (ms), RR Std (ms), HR mean (bpm), HR Std (bpm), RMSSD (ms), NN50, pNN50, RR Triangular Index, TINN (ms).In this work, six frequency domain features have been utilized. They are VLF Power (ms^2), LF Power (ms^2), HF Power (ms^2), LF norm, HF norm and LF/HF Ratio [22]. The frequency domain parameters used for assessing the stress are described in Table 1. The three frequency bands used are VLF, LF, HF and a frequency ratio LF/HF. In addition to these parameters, LF norm and

HF norm are calculated in terms of normalized units.

SVM is a popular machine learning algorithm that is widely deployed in pattern recognition, object identification,

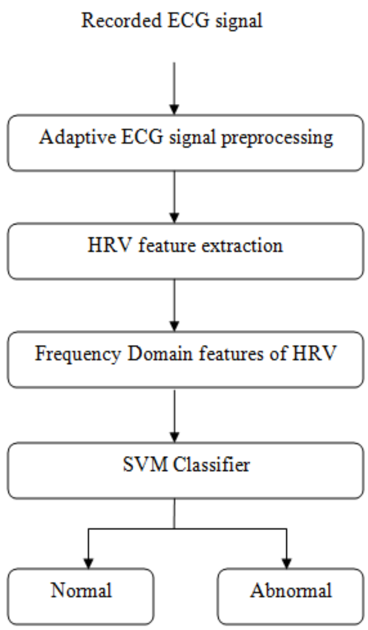


FIGURE 2. Steps involved in abnormality detection.

TABLE 1. Frequency-domain measurements used for HRV Analysis.

Variable	Unit	Description
VLF	ms^2	Power from 0 Hz to 0.04 Hz.
LF	ms^2	Power from 0.04 Hz to 0.15 Hz.
HF	ms^2	Power from 0.15 Hz to 0.40 Hz.
LF Norm	n.u.	LF power in normalized units: LF/ (Total Power-VLF)*100.
HF Norm	n.u.	HF power in normalized units: HF/ (Total Power-VLF)*100.
LF/HF Ratio	N/A	LF [ms^2]/HF[ms^2].

character recognition, image segmentation and classification [17]. SVM classifier use complex features in the above mentioned applications using clustering, classification and ranking. The separation of values and grouping is performed by the decision function between the two classes. The weight and bias values are applied in classification problems to minimize the cost function. MIT-BIH data base has been chosen for arrhythmic beat classification and abnormality detection. The detected the R waves and RR intervals are used for HRV frequency domain analysis. The frequency domain parameters listed in Table 2 are calculated for the HRV extracted preprocessed data for arrhythmic beat classification.

IV. RESULTS AND DISCUSSION

In order to detect the abnormality in ECG, preprocessing stage is followed by R-peak detection and beat classification. The simulation experiments are based on MIT-BIH arrhythmia database ECG signal for performing the simulation study, because of its wide acceptability. The real time recorded data using National Instruments (NI) DAQ also utilized for this study. The data base consists of 30-min excerpts of two-channel ambulatory ECG recordings. The database ECG signal is originally obtained by placing the electrodes on the

TABLE 2. Comparison of various classification techniques.

Technique	Signal / Feature	Classification accuracy (%)
ANN & PCA [6]	ECG	88.5%
KNN classifier [15]	HRV	90.4%
Fuzzy decision classifier [26]	HRV	91.8%
Fuzzy KNN [27]	ECG	92.5%
Neuro fuzzy [28]	HRV	94.2%
SVM Classifier (Proposed technique)	HRV	96%

chest in the first channel V1that is the standard practice in ECG recording. The recorded signal has been digitized at 540 Hz sampling rate with 11-bit resolution over a 10mV range.

All the simulation experiments were conducted using MATLAB®v. 7.12. In the simulation scenario, we choose μ for all the filters as 0.01 and the filter length as 21 for reducing the simulation time. The number of iterations for the experiment is 1500. NI LabVIEW based biomedical kit is used for extracting frequency domain features such as low frequency, high frequency, frequency ratio and normalized frequency.

Filter convergence vary in accordance to step size, it converges faster for high step size. MSE reduces in accordance with the increase in SNR of noise. MSE of 19.5 dB has been achieved for the iteration time110 in DENLMS algorithm which is superior to NLMS, transform domain (TDLMS) and delayed NLMS (DNLMS) algorithms. The filtering performance of this algorithm is observed using five MIT-BIH data base ECG signals. Figure 3 shows the extraction of clear ECG from corrupted ECG data (record 104).

The preprocessed ECG is applied to R-peak detection stage to determine the possible beats per minute. The human heart rate values vary between 60 to 100 bpm. Coiflet wavelet is used to detect the RR interval as well as possible R-peaks and beat rate obtained is 72. The wavelet coefficients are calculated and plotted for real time recorded signals and MIT-BIH database in figure 4.

Based on the Table 1, the frequency domain parameters such as VLF (ms^2), LF (ms^2), HF (ms^2), frequency ratio LF/HF, LF norm and HF norm are noted for all the feature extracted ECG data, depicted in Figure 5. National instruments (NI) biomedical kit has been utilized for the computation of frequency domain values. These values are averaged to analyze the risk using arrhythmic beat classification.

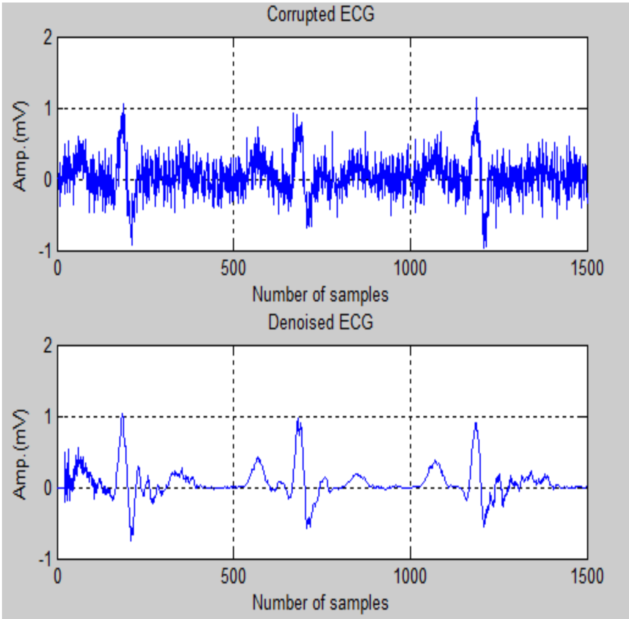
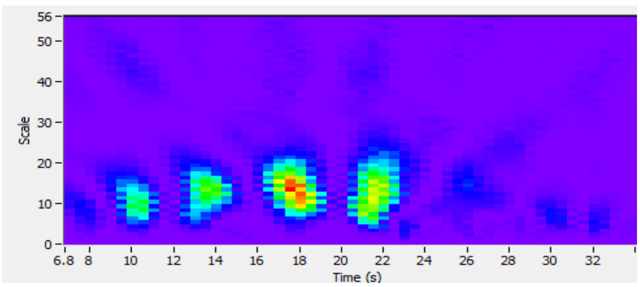
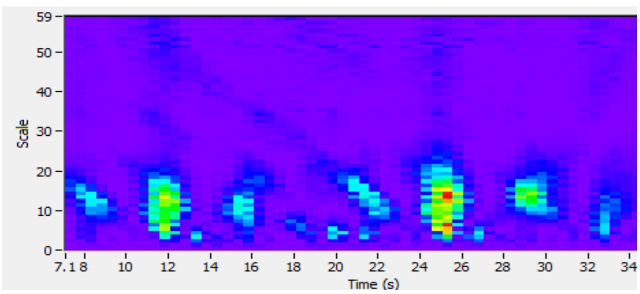


FIGURE 3. Original and denoised ECG signals using modified ENLMS algorithm.



(a)



(b)

FIGURE 4. Wavelet coefficients from RR interval for (a) MIT-BIH sample (b) Smoker.

In SVM classification, frequency domain features have been computed from the total of 200 HRV data. Different weighting values are applied over the costing function for better classification results. Threshold values are fixed for the frequency domain features VLF (ms^2), LF (ms^2), HF (ms^2), frequency ratio LF/HF, LF norm and HF norm while categorizing into normal and abnormal subjects.180 training data (90%) with signal length of 60 seconds have been used to train the SVM classifier. After training, 20 testing data (10%) were used to validate the accuracy of the classifier. The classification accuracy is calculated using correctly classified signals from the total number of signals considered for classification.

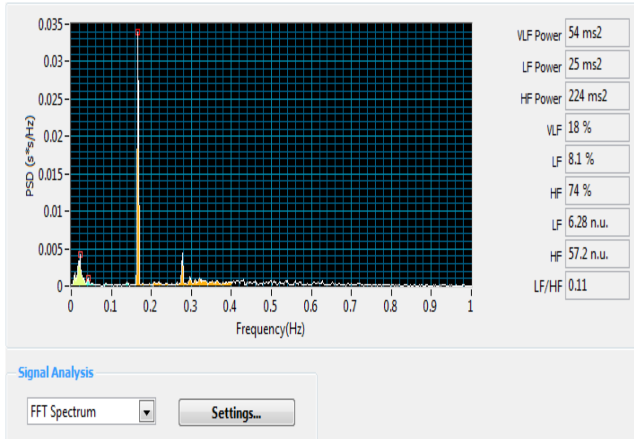


FIGURE 5. Obtained frequency domain features using NI biomedical kit.

In the SVM classification based abnormality detection method, extracted R peaks are considered after performing ECG signal preprocessing. Few existing techniques are time-consuming and require complex computations. In addition, morphological ECG features are not feasible while dealing with noisy data. Various techniques is compared in Table 2 to categorize the arrhythmic risk abnormal and normal subjects. Some of the exiting classification techniques chosen which are based on principal component analysis (PCA), knowledge based system and support vector machine (SVM). In these techniques, ECG, blood volume, HRV parameters were used. The maximum classification accuracy of 96% has been achieved using these techniques. But the experimental result of SVM based classifier gives a maximum accuracy of 96% on classifying normal and arrhythmic risk abnormal subjects.

V. CONCLUSION

The obtained results of the preprocessing, feature extraction and classification are used to conclude the proposed technique. In ECG signal preprocessing, DENLMS algorithm based adaptive filter is utilized to obtain better filtering performance with low computational complexity. In R-peak detection, Coiflet wavelet is used to extract all the possible R-peaks and provides the more accurate beat rate. The obtained beat rate and HRV Frequency domain features are applied to SVM classifier for arrhythmic beat classification which is simpler than other machine learning approaches. Various classification techniques based on PCA, ANN, knowledge based system, KNN and SVM are used using parameters such as ECG and HRV. The maximum classification accuracy of 94.2% has been achieved using these techniques. But the experimental result of SVM based classifier gives a maximum accuracy of 96 % on classifying normal and arrhythmic risk abnormal subjects.

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