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Electrocardiogram Signal Modeling Using Adaptive Framework Based SVM Classification Method

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Abstract— Automatic electrocardiogram (ECG) signal classification plays a significant role in the clinical applications, to overcome the problems occur during manual annotation of the ECG recordings. The ECG beat morphologies and disease states cannot be defined easily by a single representation, since it can vary greatly for each person. This paper proposes ECG signal modeling using adaptive framework based Support Vector Machine (SVM) classification method. The main objective of the SVM classification method is to select the best cardiac parameter. Filtering of the ECG signal is performed using Lowpass Butterworth filter. Feature extraction is performed using Wavelet-based transform. The Automatic feature selection algorithm is applied for determining the best feature subset for some criterion. The heart rate (HR) is calculated based on the extracted features of the ECG signal. Detection of the cardiovascular abnormalities is performed based on the HR calculation. The proposed method achieves efficient detection of cardiovascular abnormalities, by eliminating the fault signals and reducing the error signals.

Index Terms— Electrocardiogram (ECG) Signal, Feature Extraction, Interacting Multiple Modeling (IMM) Method, Heart Rate (HR), Support Vector Machine (SVM) Classification and Wavelet-based transform

1. INTRODUCTION

Electrocardiogram is a simple and non-invasive procedure that records the electrical activity of the heart. Deviation in the normal electrical patterns of the heart indicates various cardiac disorders. Recently, sequential Bayesian methods, such as particle filtering (PF) [1], Kalman filtering (KF) [2] and extended Kalman filtering (EKF) and have been applied to ECG signal processing and modeling, to estimate heart rate, calculate the heart rate variability and remove noise and interference artifacts. The main drawback of the PF principle is computational complexity for the large state dimension. The orthonormal function model (OFM) is presented to identify the underlying features of the ECG waveforms. The Chebyshev polynomial is selected among the set of all orthonormal functions, because the Chebyshev polynomial can uniformly approximate a broad class of functions and provide the convergence among all ultra-spherical polynomials. The orthonormal function model cannot detect the fault in the ECG signal. The heart rate cannot be taken correctly by using the ECG signal processing techniques.

This paper proposes an adaptive framework based support vector machine (SVM) classification method for the efficient modeling of the ECG signal. On the other hand, recent contributions to baseline wandering removal have proposed a wide range of different techniques, including nonlinear filter banks, wavelet denoising, adaptive filtering and empirical mode decomposition. Moreover, some researchers tried to suppress baseline wander using high-pass filtering, which introduces either nonlinear phase distortion or amplitude distortion. In order to overcome these difficulties, a low-pass Butterworth filter is utilized for the efficient removal of baseline wander in the ECG signal.

Real ECG signals are initially processed using a Butterworth filter, to eliminate baseline wander and power-line interference. Wavelet based features will be extracted from the ECG signal. The Daubechies wavelet is found to be the most suitable for the analysis of ECG signals. The DWT has higher compression ratios to avoid blocking artifacts and allows good localization both in time and the spatial frequency domain. To determine the best feature subset for some criterion, the automatic feature selection algorithm is applied to the complete feature space. The cardiovascular abnormality detection is performed based on heart rate (HR) calculation. The HR is calculated from the extracted features of the ECG signal by finding the inverse of RR-interval. The normal range of HR is 60-120 beats per minute (BPM). The formula used to calculate the heart rate (HR) is Heart Rate = [360/ (RR-interval in samples)] * 60 beats/min. The calculated HR value is compared with the normal range to detect the cardiovascular abnormalities. The slow and fast heart rate value determines the cardiovascular abnormalities such as bradycardia and tachycardia, respectively.

In the proposed method, adaptive framework based support vector machine (SVM) classification method is used due to their robustness even in the absence of a rich set of training examples. Since the SVMs work well even in high-dimensional spaces, no external feature extractor is required to reduce the dimensionality of the ECG signal. The need for a time-consuming feature extraction stage is eliminated by using the SVM classification method. In fact, SVMs can efficiently extract features within their own architecture using kernel functions. The appeal of SVMs lies in their strong connection to the underlying statistical learning theory. According to the structural risk minimization principle, a function that can classify the ECG signal accurately. This signal classification function will generate a high-quality output signal, irrespective of the dimensionality of the input space. As a result, the adaptive framework based SVM classification method provides efficient detection of cardiovascular abnormalities, by eliminating the fault signals and reducing the error signals.

The paper is organized as follows: Section II describes the related work. Section III illustrates about the ECG signal

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modeling using adaptive framework based SVM classification method. Section IV shows the performance analysis and Section V describes the conclusion.

2. RELATED WORK

Traditionally ECG signal analysis is performed based on time domain method. But this method cannot be able to study all features of ECG signals. Hence, frequency representation of the ECG signal is required. To achieve this, Fast Fourier Transform (FFT) technique is applied. But the FFT technique does not provide the information about the exact location of the frequency components with respect to time. Since the frequency content of the ECG signal varies with respect to time, there is a need for accurate definition of the ECG frequency content. The short term Fourier Transform (STFT) is applied for this purpose. But the major drawback of the STFT is the time-frequency precision of the STFT is not optimal. Among various time-frequency transformations, the wavelet transform is found to be simple and more valuable. The wavelet transformation is performed based on the set of analyzing wavelets that allow the breakdown of the ECG signal in a specific set of coefficients. The wavelet coefficient obtained from the wavelet transformation matches with the measurement of the ECG components in the time segment and frequency band.

Lin et al [1] proposed sequential Bayesian methods to estimate the waveforms sequentially for each beat, for detecting beat-to-beat waveform variations, instead of processing the multiple-beat signal blocks. The Bayesian signal models consider the previous beats as prior information. A block Gibbs sampler showing fast convergence rate is proposed irrespective of the robust local dependencies in the ECG signal, for the estimation of unknown parameters of these Bayesian signal models. The sequential Monte Carlo method is utilized with a marginalized particle filter, to estimate the unknown parameters of the dynamic model efficiently. Significant improvement in the detection rate and delineation accuracy can be achieved in comparison with the traditional methods, while providing promising approaches for sequential P and T wave analysis.

Moradi et al [2] suggested the usage of adaptive Kalman filter and signal averaging for the ECG signal enhancement. Kalman filter improves the signal to noise ratio (SNR) to 21.49 dB by applying averaging approach. Kalman filter with adaptive noise covariance estimation is evaluated on a real ECG signal to assess whether the filter is capable of enhancing the SNR of this signal, while detecting clinically relevant morphological variations in the ECG. Seera et al [3] proposed examination of medical classification problems using ECG and auscultatory blood pressure (Korotkoff) signals. Classification of the medical data sets is performed using nine machine learning models. The performance metrics including accuracy, sensitivity and specificity are computed. The robustness of the classifiers against noise is evaluated by generating noisy data sets, along with the original data sets. The performance statistics is computed using 10-fold cross validation method, to ensure statistically reliable results related to the ECG classification. Good accuracy rates with noisy data sets can be achieved with the machine learning models, along with the better performance of the logistic regression models with the original data set. Bodisco et al [4] suggested the extraction of key features of the ECG signal, using Markov-chain Monte Carlo statistical modeling. The wave morphology and noise levels are detected, by examining the proposed Markov-chain Monte Carlo statistical modeling approach with a realistic computer generated ECG signal.

Wang et al [5] presented an effective ECG arrhythmia classification scheme, for discriminating eight different types of arrhythmia. The feature reduction method is utilized to find out the significant features from the ECG beats and improve the accuracy of the classifier. The probabilistic neural network (PNN) is trained to serve as a classifier, to discriminate different types of arrhythmia from the ECG beats. The proposed ECG arrhythmia classification scheme improves the average classification accuracy. Edla et al [6] proposed the utilization of sequential Markov chain Monte Carlo (SMCMC) filter for the ECG modeling process. Simultaneous model selection is performed, by adaptively choosing from different representations based on the nature of the data. Tracking of various types of ECG morphologies can be achieved by the proposed method. The estimated model parameters are utilized for the classification of the ECG signals, with four different types of arrhythmia and normal sinus rhythm.

Raghavendra et al [9] proposed a dynamic time warping (DTW) distance based method for the efficient classification of arrhythmic ECG beats. The performance of the DTW method is validated with the ECG beats of various types of arrhythmia selected from the arrhythmia database. The performance of the DTW approach is higher when compared to the naive Bayes classifier, based on the comparison result of the DTW approach with the relative band spectral power. Furthermore, the performance of the DTW approach is verified on down-sampled ECG beats, for improving the performance rate of the proposed DTW method. It is observed that there is no deterioration in the performance of the DTW approach, even after sub-sampling of the ECG beats. The DTW with sub-sampling can achieve real-time arrhythmia detection in the telemedicine applications, for the continuous monitoring of ECG records of the cardiac patients.

Statistical models were developed for the adaptive modeling and estimation of the ECG signal parameters using the sequential Bayesian techniques. A simple Bayesian ML classifier is implemented to classify between different cardiac conditions. The Bayesian models do not require user-defined parameters and early-stage processing to obtain a priori ECG signal information for the initialization of the filter or ECG fiducial point delineation, since the Bayesian model is adaptive to changes in the ECG signal morphology. The estimated model parameters provide the features that can be utilized for the automatic classification of the cardiac arrhythmia and speedy diagnosis of the cardiac arrhythmia, while reducing the need for manual annotation.

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The cardiac arrhythmia cannot be detected efficiently by the traditional ECG modeling approaches, since the ECG beat morphologies and disease states cannot be defined easily by a single representation. This paper proposes ECG signal modeling using adaptive framework based Support Vector Machine (SVM) classification method, to select the best cardiac parameter. The SVM classification method provides efficient detection of cardiovascular abnormalities, by eliminating the fault signals and reducing the error signals.

3. ECG SIGNAL MODELING USING ADAPTIVE FRAMEWORK BASED SVM CLASSIFICATION METHOD

The ECG signal modeling is performed using the adaptive framework based SVM classification method for the efficient detection of cardiac arrhythmia such as Tachycardia, Bradycardia, etc., Fig.1 shows the block diagram of the ECG modeling process. Real ECG signals are initially processed using a Lowpass Butterworth filter, to eliminate baseline wander and power-line interference. Wavelet based features will be extracted from the ECG signal. The Daubechies wavelet is found to be the most suitable for the analysis of ECG signals. Different abnormalities result in different changes in the coefficients. The wavelet transform is defined as a convolution of the wavelet function *ψ(t) with the* signal *x(t)*. Orthonormaldyadic discrete wavelets are related with the scaling functions φ(t). The convolution of the scaling function with the signal is performed to produce approximation efficient S. The discrete wavelet transform (DWT) can be written as

$$T_{m,n} = \int_{-\infty}^{\infty} x(t)\psi_{m,n}(t)\,dt \qquad (1)$$

The DWT has higher compression ratios to avoid blocking artifacts and allows good localization both in time and the spatial frequency domain. The best feature subset for some criterion is determined, by applying the automatic feature selection algorithm to the complete feature space, while varying the number of selected features from 1 to m.

The cardiovascular abnormality detection is performed based on heart rate (HR) calculation. The HR is calculated from the extracted features of ECG signal by finding the inverse of RR-interval which is the time difference between two consecutive R-peaks present in every QRS complex. The normal range of HR is 60-120 beats per minute (BPM). The formula used to calculate the heart rate (HR) is Heart Rate = [360/ (RR-interval in samples)] * 60 beats/min. The calculated HR value is compared with the normal range to detect the cardiovascular abnormalities. The slow and fast heart rate value determines the cardiovascular abnormalities such as bradycardia and tachycardia, respectively. The ischemic episode detection performance is measured in terms of sensitivity (Se) and positive predictive accuracy (PPA). The sensitivity parameter measures the ability to detect ischemic episode, whereas positive predictive accuracy provides the estimation likelihood that the detected episode is a true Ischemic episode.

$$Se(\%) = TP(TP + FN) \times 100 \qquad (2)$$

$$PPA(\%) = TP(TP + FP) \times 100 \qquad (3)$$

Where TP = True Positive (correctly detected event)
FP = False Positive (erroneously detected non-event)
FN = False Negative (erroneously missed event)

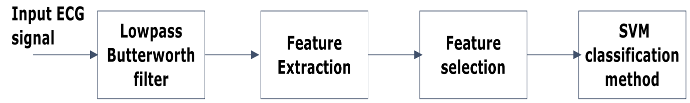

Fig.1 shows the block diagram of the proposed ECG modeling process.

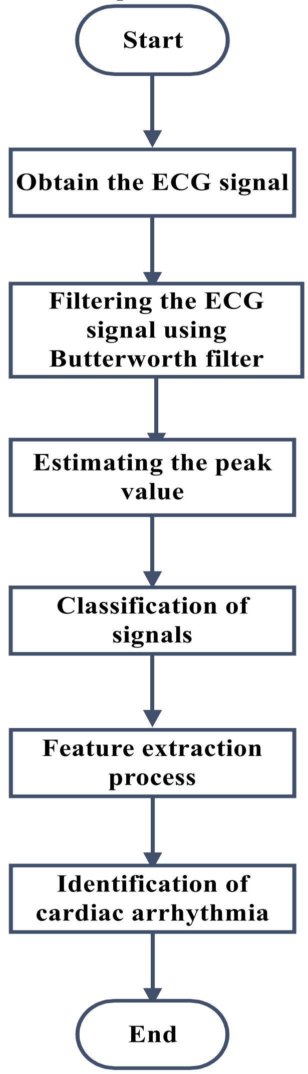

Fig.2 Flowchart of the proposed ECG modeling process.

Fig.2 shows the flowchart of the proposed ECG modeling process using the SVM classification method.

3.1 ECG CLASSIFICATION USING INTERACTING MULTIPLE MODELING (IMM) METHOD

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The concept of multiple switching dynamic models is relevant in many applications as many dynamic systems are best characterized by a set of possible modes of operation rather than a single mode. ECG signals fit well into this framework due to their dynamical nature and time-varying morphologies. The IMM algorithm can be used to estimate states and modes evolving according to a first-order Markov process. The IMM algorithm performs three main operations at each time step: interaction, filtering, and combination. During interaction step, the mixing probabilities $\mu_{t-1}^{(a|b)} = \Pr(m_{t-1} = a | m_t = b, S_{t-1})$ is calculated using the mode probabilities $\mu_{t-1}^{(a)}$. m_t is the mode at time t and S_{t-1} is the set of measurements. The filtering operation is considered as a bank of mode-matched filters, whose input parameters are calculated using the mixing probabilities. Then, prediction and update step is performed to provide an updated state parameter estimate, $\hat{y}_{t|t}^{(b)}$, under the corresponding mode of operation, a=1,……,N and b=1,…..,N. Additionally, the mode likelihoods $\Lambda_t^{(b)} = p(s_t | S_{t-1}, m_t = b)$ using the Gaussian approximation. The posterior mode probabilities are then updated as

$$\mu_t^{(b)} = \Delta_t^{(b)} \sum_{a=1}^{N} \pi_{ab} \mu_{t-1}^{(a)} / \sum_{b=1}^{N} \Lambda_t^{(b)} \sum_{a=1}^{N} \pi_{ab} \mu_{t-1}^{(a)} \tag{4}$$

During combination, the estimates from the different mode-matched filters are weighted by the corresponding mode probabilities and aggregated to calculate the overall estimate of the system parameters as

$$\hat{y}_{t|t} = \sum_{b=1}^{N} \mu_t^{(b)} y_{t|t}^{(b)} \tag{5}$$

Algorithm: IMM ECG Modeling

Step:1 Remove power-line interference and baseline wander from the ECG signal using a Butterworth filter

Step:2 Divide the ECG signal into beats. For each ECG beat with S_b samples at time t, t=1,…, S_b, using measurement z_t and state parameter vector $y_t = [\mathrm{v}_{t,0} \ldots \mathrm{v}_{t,N}]^T$ (N[th] order polynomial coefficients) , perform the following steps

a) Initialize the polynomial coefficients and the transition and mode probabilities for the linear, quadratic, and cubic order polynomial ECG models
b) Compute the IMM mixing probabilities and input parameters for the N=3 mode-matched filters using the transition, mode probabilities and polynomial coefficients from time (t-1)
c) Estimate the state vector for the N=3 modes using the Kalman filtering (KF), ECG state-space model, input parameters from the initialization step and ECG measurement; calculate the probabilities for the polynomial modes using posterior mode probabilities
d) Obtain the noise-free reconstructed ECG signal using the combined polynomial coefficient estimate with the measurement model for the time-do-main ECG signal.

Modeling of the ECG signals using the IMM framework provides an approach to adaptively utilize different order polynomial representations for the ECG signals depending on their morphology.

3.2 ADAPTIVE FRAMEWORK BASED SVM CLASSIFICATION METHOD

The Support vector machine (SVM) classification method shows the excellent performance in the high-dimensional data classification process. During the data classification process, the SVM kernel parameter significantly influences the data classification accuracy. By determining a set of support vectors associated with the set of training inputs that define a hyper plane in the feature space, the SVM classifies data with different class labels. The key concept of SVMs includes the usage of hyper planes to define the decision boundaries between the data points of different classes. SVMs can solve both simple and linear classification tasks, and also more complex and nonlinear classification problems.

SVMs can handle both separable and non-separable problems in the linear and nonlinear case. The original data points from the input space are mapped to a high-dimensional or even infinite-dimensional feature space, such that the classification problem is simplified in the feature space. The data mapping can be done with a suitable choice of akernel function. The purpose of the Support Vector classification is to develop an efficient way of learning optimal separating hyper planes in a high dimensional feature space.

Let $Y = \{(\mathrm{a}_j, \mathrm{b}_j)\}_{j=1}^{m}$ be a set of m training samples, where $a_j \in S^n$ is n-dimensional sample in the input space and $b_j \in \{-1,1\}$ is the class label of the sample a_j. SVM finds out the optimal separating hyperplane (OSH) with the minimal classification errors. The linear separation hyperplane is in the form of

$$f(\mathrm{y}) = \mathrm{W}^T a + B \tag{6}$$

Where W is weight vector and B is bias. In a support vector machine, the optimal hyperplane is obtained by maximizing the generalization capacity of the SVM. However, if the training data are not linearly separable, the obtained classifier may not have high generalization capacity, even though the hyperplanes are determined optimally. To enhance the linear separability, the original input space is mapped into a high-dimensional dot-product space called the feature space. Using the nonlinear vector function, $\rho(\mathrm{y}) = (\rho_1(\mathrm{y}), \ldots, \rho_1(\mathrm{y}))^T$ that maps the n-dimensional input vector y into the l-dimensional feature space, the optimal separating hyper plane in the feature space is given by

$$f(\mathrm{y}) = \mathrm{W}^T \rho(\mathrm{y}) + B \tag{7}$$

The decision function for a test data set is:

$$D(y) = \text{sign}(W^T \rho(y) + B) \quad (8)$$

The optimal hyperplane can be found by solving the following quadratic optimization problem:

$$Minimize \frac{1}{2}\|W\|^2 + C\sum_{j=1}^{m}\varphi_j \quad (9)$$

subject to $b_j(W^T \rho(y_j) + B) \geq 1 - \varphi_j$

$$\varphi_j \geq 0, j = 1, ..., m$$

φ_j is slack variable for obtaining a soft margin while variable C controls the effect of the slack variables. Separation margin increases by decreasing the value of C.

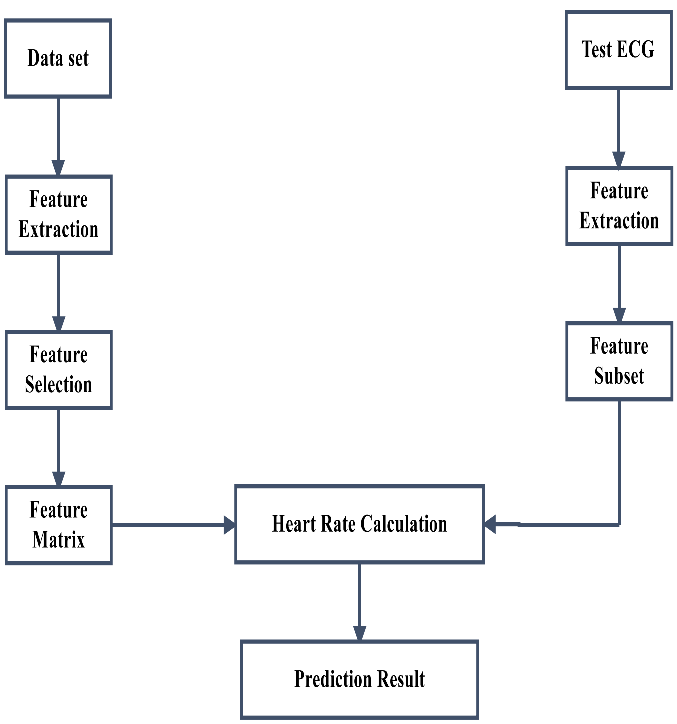

Fig.3 System architecture of the proposed ECG modeling process.

Fig.3 shows the system architecture of the ECG modeling process.

4. PERFORMANCE ANALYSIS

The simulation results show the input ECG signal and filtered ECG signal. The moving average filter and filtered, smoothed and processed ECG signal along with R wave, S wave, T wave, R adaptive threshold and S wave and raw ECG signal were also shown in the simulation results. The table I shows the comparison between the percentage level of the performance metrics such as accuracy, sensitivity and specificity of the existing Sequential Bayesian Model and proposed SVM classification method. Fig.4 shows the input ECG signal.

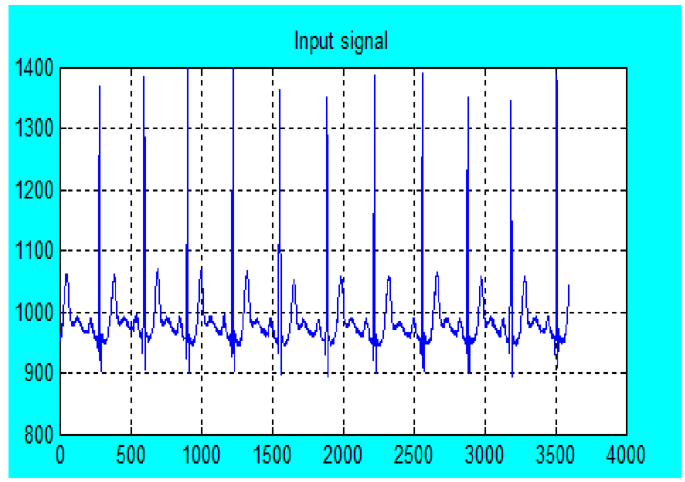

Fig.4 Input ECG signal

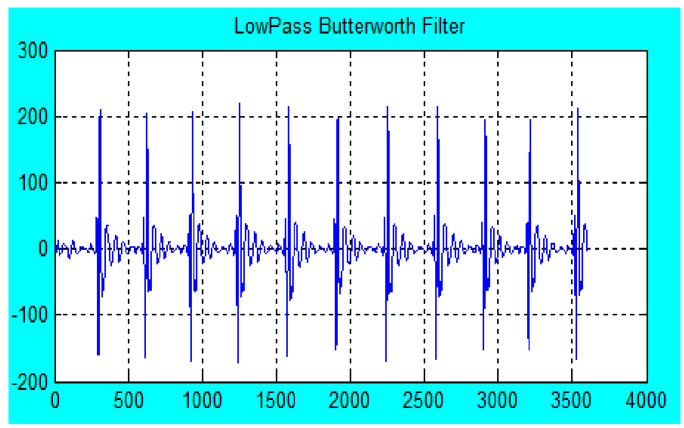

Fig.5 Filtered ECG signal

Fig.5 shows the filtered ECG signal. The ECG signal is filtered using the Lowpass Butterworth filter, for the efficient elimination of baseline wander and power-line interference.

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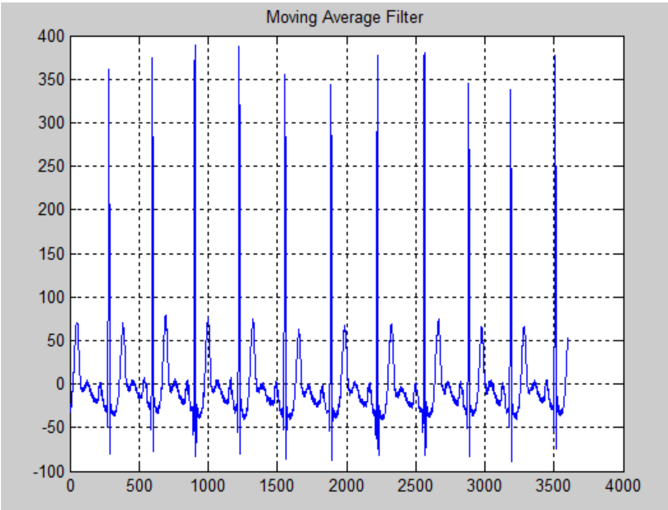

Fig.6 Moving Average Filter

Fig.6 shows the filtering process of the ECG signal, with a moving average filter.

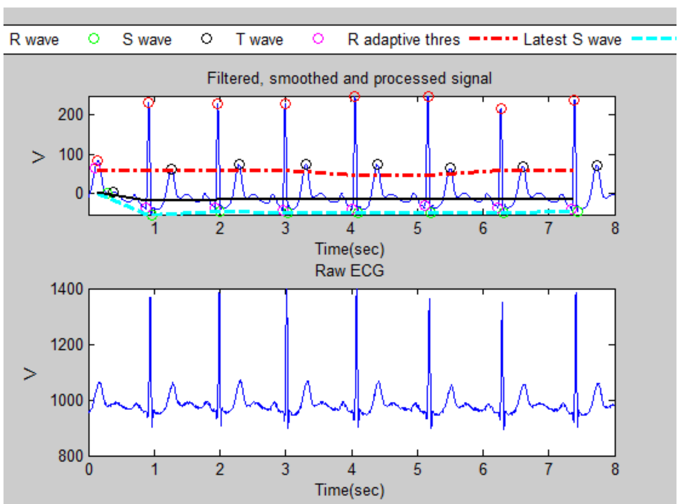

Fig.7 Filtered, smoothed and processed signal, and raw ECG signal

Fig.7 shows the raw ECG signal and the filtered, smoothed and processed signal, along with R wave, S wave, T wave, R adaptive threshold and S wave. The Low pass Butterworth filter is used for filtering the ECG signal, to remove baseline wander and power-line interference and obtain a smooth ECG signal without any interference.

Table.I shows the comparison between the performance metrics of the Sequential Bayesian Model and SVM Classification method.

Performance Metrics	Sequential Bayesian Model	SVM Classification Method
Accuracy (%)	43.875	57.1429
Specificity (%)	52.876	66.6667
Sensitivity (%)	38.558	50

The Table I shows the comparison between the percentage level of the performance metrics such as accuracy, sensitivity and specificity of the Sequential Bayesian Model and SVM classification method. From the comparison result, the percentage level of the performance metrics of the proposed SVM classification method is higher than the existing Sequential Bayesian model. Efficient detection of the cardiac arrhythmia such as Bradycardia and Tachycardia is achieved due to the elimination of the fault signals and the reduction of the error signals.

5. CONCLUSION

Thus, the proposed method achieves efficient analysis of the ECG signal. The adaptive framework based SVM classification method provides efficient detection of cardiovascular abnormalities, by eliminating the fault signals and reducing the error signals. The percentage level of the performance metrics such as accuracy, sensitivity and specificity of the proposed SVM classification method is improved when compared to the performance metrics of the existing Sequential Bayesian Model. The computational cost is reduced in terms of both memory and runtime, since the proposed method requires only primitive and simple mathematic operators.

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