A Reliable Arrhythmias-Recognition Scheme Via Wavelet and Multiclass Support Vector Machine

Magdi B. M. Amien, Tamadur El-Khansa Japir

Abstract*: Heart diseases (HD) are the number one cause of death globally, more people die annually from HDs than from any other cause, according to World-Health-Organization (WHO) 7.3 million were died due to coronary heart disease in 2008. Electrocardiogram (ECG) interpretation is most widely used to detect the abnormality of the heart. A reliable computer programs could lead to enhanced visual interpretation, and significant-increase of diagnosis-efficiency. This study introduced a novel method for ECG classification; fifteen different records of five rhythms from "MIT-BIH" Arrhythmia Database have been used to evaluate the implemented algorithms. The proposed approach consists of three distinct stages. In the first stage a preprocessing of different-steps is done to remove the baseline wander, power line interference and to enhance morphological properties. Secondly Daubechies are chosen and implemented as mother-wavelet-function to extract ten features of ECG signals, in the final stage Support-Vector-Machines (SVM), has been used as Multi-class classifier and decision making algorithm. The performance of the proposed method has bees evaluated in terms of accuracy, and specific accuracy. The experimental results have shown that the proposed system achieves validity as competitive results quality-wise, and the accuracy-rate of classification of Normal sinus Rhythm (N), Bundle Branch Block (RBBB), Atrial Premature Beat (APB), 3Premature Ventricular Contraction (PVC), Fusion Heart Beats (F), and Unclassified Heart Beats (P) were 90.0%, 100%, 66.6%, 100%, 100%, and 100%, respectively.

***Index Terms*: Arrhythmias classification, Wavelet, MSVM.**

I. INTRODUCTION

Cardiac failure is the most common reason of sudden death nowadays, more people die annually from heart-diseases than from any other cause, so early-phase detection and continuous monitoring of heart arrhythmias became very important and highly needed to allow effective treatment and save the patient's life. Heart diseases can be detected by means of visual interpretation and analysis of electrocardiogram (ECG). Several research-studies have shown the possibility of analysis ECG and detection of heart abnormalities' based-on mathematical methods and computational techniques, but still there are many aspects, issues, , and challenges to be studied and addressed to propose and develop a reliable, novel, full-automated computational system for Arrhythmias detection. A perfect, accurate arrhythmias classification algorithm depends on the extracted ECG-features that discriminate properly between heart-arrhythmias classes. ECG Feature Extraction plays a significant role in diagnosing most of the cardiac diseases. One cardiac cycle in an ECG signal consists of the P-QRS-T waves.The morphologies, amplitudes and intervals value of P-QRS-T segment determines the functioning of heart of every human [1]. In literature many ECG-feature extraction techniques were introduced and developed over the years, the features could be extracted based-on time domain parameters, frequency domain characteristics, time-frequency domain, and Statistical Properties. This study introduced a novel method for ECG classification; fifteen different records of five rhythms from "MIT-BIH" Arrhythmia Database have been used to evaluate the implemented algorithms. The proposed approach consists of three distinct stages. In the first stage a preprocessing of different-steps is done to remove the baseline wander, power line interference and to enhance morphological properties. Secondly Daubechies are chosen and implemented as mother-wavelet-function to extract ten features of ECG signals, in the final stage Support-Vector-Machines (SVM), has been used as Multi-class classifier and decision making algorithm. The remainder of this paper is organized as follows. Section two outlined, the reviewed related literature, then the proposed methodology and the description of the exact steps that had been taken to address hypotheses was presented and explained in section three. In section four the study result were presented and discussed. Finally the paper was concluded in section five.

II. RELATED STUDIES

Arrhythmias detection and classification systems was introduced and used since early 1960s, [2], hundred of thesis, journal papers, conferences, and websites were found to be under ECG/Arrhythmias analysis, detection and classification; these literature cover the whole spectrum of the concerned topic during the last decays, after detailed-revision; nine paper out of theses studies were selected and briefly discussed and summarized. A. B. Ramli, and P. A. Ahmad (2003); in their paper entitled "Correlation analysis for abnormal ECG signal features extraction", they use Cross-correlation analysis to measures the similarity between the two signals and extracts the information present in the signals, test results suggested that the proposed technique could effectively

Manuscript Received on July 2014.

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extract features, which differentiate between the types of heart diseases analyzed and also for normal heart signal [3]. In (2003) C. Alexakis, and others utilized combination of artificial neural networks (ANN) and Linear Discriminant Analysis (LDA) techniques for feature extraction. Five ECG features namely RR, RTc, T-wave amplitude, T-wave skew, and T wave kurtosis were extracted. [4]. A approach based on Wavelet Transform and Support Vector Machines was introduced by Qibin Zhao, and Liqing Zhan in (2005); concurrently, they used autoregressive modeling (AR) to get hold of the temporal structures of ECG waveforms, the performance of their approach achieved overall accuracy of 99.68% [5]. S. Z. Mahmoodabadi, and others in (2005) were concentrated on extracting the ECG features based on wavelet filter which has scaling-function further intimately similar to the shape of the ECG signal. The foremost step of their approach was to de-noise the ECG signal by removing the equivalent wavelet coefficients at higher scales. Then, QRS complexes are detected and each one is used to trace the peaks of the individual waves, including onsets and offsets of the P and T waves which are present in one cardiac cycle.[6]. An algorithm introduced by Mazhar B.Tayel and others using Wavelet Transformation And Neural Network was developed in (2006) to classify Heart-disease, their results showed that the classification accuracy of the introduced classifier was up to 92%.[7]. F. Sufi, S. Mahmoud, I. Khalil in (2008).proposed a truly A new ECG obfuscation method: A joint feature extraction & corruption approach, which uses cross correlation based template matching approach to distinguish all ECG features followed by corruption of those features with added noises. they considered three templates and three noises for P wave, QRS Complex and T wave comprise the key, which is only 0.4%-0.9% of the original ECG file size. To conclude, the experiments carried on with unimaginably high number of noise combinations the security strength of the presented method was very high[8][9]. Fatemian, S.Z. and others developed a new ECG feature extractor for biometric recognition based-on a new wavelet framework witch was capable of handling noise and outliers, and managing ECGs regardless of the heart rate (HR) which renders making presumptions on the individual's stress level unnecessary. The substantial reduction of the template gallery size decreases the storage requirements of the system appreciably. Additionally, the categorization process is speeded up by using dimensionality reduction techniques such as PCA or LDA. [10]. In 2013, Branislav Vuksanovic & Mustafa Alhamdi proposed an AR-based Method for ECG Classification and Patient Recognition, after pre-processing, detected QRS, and AR parameters were extracted to clasifiy the corresponding signals[11].

III. THE PROPOSED APPROACH

If you are using this section describes the design and implementation of the proposed approach. Notice that modeling and simulation development of the system has been done in Matlab. Fig. (1) bellow shows the functional block diagram of the introduced approach, it consists of three stages; namely: Preprocessing, Feature extraction, and Arrhythmia classification.

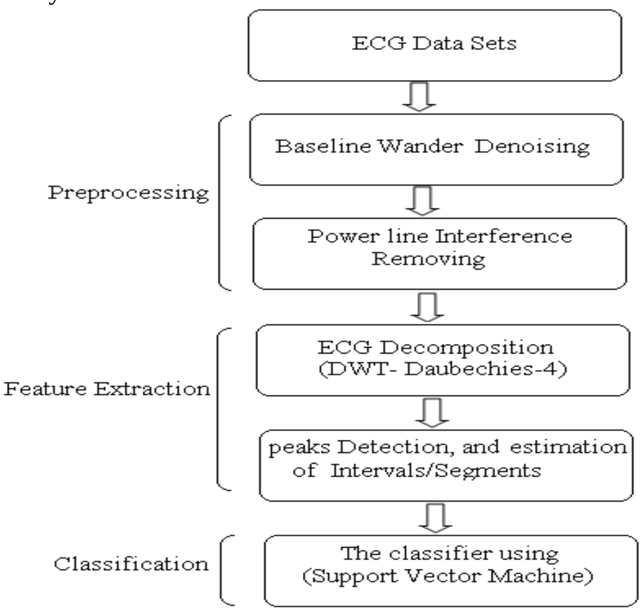

Fig. (1) Proposed Approach's Functional Block Diagram

A. Preprocessing

Signal preprocessing commonly involves removing noises, such as baseline wander, power-line interference, electrode motion artifacts, and electromyography (EMG) noise. To remove baseline wander there are two considerations to design such type of filters; cut off frequency of the filter and phase response . To eliminate the baseline wander a third-order digital highpass Butterworth filter has been designed and implemented with a cutoff frequency of fc> 0.67 Hz, this The cut off frequency is related to heart rate which should be less than the lowest frequency component in the ECG , Lowest frequency contained in the ECG is approximately 0.67 Hz [10], Butterworth filters was used because it has a short time delay, and primary used to off-line processing. To eliminate the power-line interference a second-order bandstop IIR-Butterworth filter has been designed and implemented according to the following characteristics:

$$w_h = 2\pi f_h = 2\pi\left(f_c + \frac{bp}{2}\right) \quad (1)$$

$$w_l = 2\pi f_l = 2\pi\left(f_c - \frac{bp}{2}\right) \quad (2)$$

$$w_{d0} = 2\pi f_{d0}\, 2\pi(f_c) \quad (3)$$

$$T = 1/fs \quad (4)$$

Where:

fc Center frequency

bp Pass-band width

fs Sampling frequency

Applying the three steps of the IIR fitter design approach, it follows that:

$$w_{ah} = \frac{2}{T}\tan\left(\frac{w_h T}{2}\right) \quad (5)$$

$$w_{al} = \frac{2}{T}\tan\left(\frac{w_l T}{2}\right)$$

(6)

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$$w_0 = \frac{2}{T}\tan\left(\frac{w_{do}T}{2}\right) \quad (7)$$

$$w_{sh} = \frac{2}{T}\tan\left(\frac{(fc+\frac{sb}{2})*\frac{2\pi}{fs}}{2}\right) \quad (8)$$

$$w_{sl} = \frac{2}{T}\tan\left(\frac{(fc-\frac{sb}{2})*\frac{2\pi}{fs}}{2}\right) \quad (9)$$

Then, carrying out the prototype transformation (lowpass to band-stop) using the first-order lowpass prototype filter given by:

$$H_p(s) = \frac{1}{(s+1)} \quad (10)$$

It follows that:

$$H(s) = \frac{s^2 + w_0^2}{(s^2 + Ws + w_0^2)} \quad (4.10)$$

Substitute the values w_0^2 and W by their values

Hence, applying the BLT lead to obtain the transfer function H(z)

B. Extracting Features

Extracting ECG Features is the key issue and the main component of any classification system, it is a technique involves qualitative-selection of value-wise and meaningful data, results in a much reduced, smaller and richer size of information. ECG wave commonly change their statistical properties over time, tending to be non stationary[12]. ECG is interpretation of the electrical activity of the heart over a period of time, It picks up electrical impulses generated by the polarization and depolarization of cardiac tissue and translates into a waveform. A typical ECG tracing of the cardiac cycle (heartbeat) consists of a P wave, a QRS complex, a T wave, and a U wave, which is normally invisible in 50 to 75% of ECGs because it is hidden by the T wave and upcoming new P wave [13] fig. (2). The discrete wavelet transform (DWT) uses filter banks to perform the wavelet analysis. The discrete wavelet transform decomposes the signal into wavelet coefficients from which the original signal can be reconstructed again. The wavelet coefficients represent the signal in various frequency bands. The DWT is sufficient for most practical applications and for the reconstruction of the signal. The DWT provides enough information, and offers a significant reduction in the computation time. Here, we have discrete function f (n) and the definition of DWT is given by:

$$W(a,b) = c(j,k) = \sum_{n=z} f(n)\Psi j,k(n) \quad (11)$$

Where Ψj,k(n) is a discrete wavelet defined as:

$$\Psi j,k(n) = 2^{-j} * \Psi(2^{-j}n - k) \quad (12)$$

The idea behind wavelets is to analyze according to scale. Wavelets are functions that satisfy certain mathematical requirements and are used in representing data or other functions. Wavelet algorithms process data at different scales or resolutions. If we look at a signal with a large window, we would notice gross features. Similarly, if we look at a signal with a small window, we would notice small features. The result in wavelet analysis is to see both the forest and the trees, so to speak. DWT has different families such as Haar Wavelet, Daubechies Wavelets, Symlets Wavelets, Coiflets Wavelets, Biorthogonal Wavelets, Meyer Wavelet, Mexican Hat Wavelet and so on. In this study Daubechies wavelet-transform was used as ECG feature-extractor, wavelet transforms are a powerful tool provide simultaneous time and frequency information. The wavelet transform decomposes the signal into a set of frequency bands. Daubechies are a family of wavelets that form an orthonormal basis via a multiresolution analysis and are optimal in a certain sense, usually Daubechies are chosen to have the highest number A of vanishing moments, there are two naming schemes in use, DN using the length or number of taps, and dbA referring to the number of vanishing moments. So D4 and db2 are the same wavelet transform. In this study a set of ten ECG-features including amplitudes, intervals, segments, and signal energy ware extracted using Daubechies-4. The R peaks were detected at the decomposed signals. 60% of the max-value of the actual signal are were used as thresh-hold to represent R peaks, according to R peaks the other peaks were detected by using minimum and maximum algorithm.

C. Classifier

In this phase the ECG signal is classified according to its ten extracted-features based-on Multi-Class Support Vector Machine (MSVM. Multiclass SVM aims to assign labels to instances by using support vector machines, where the labels are drawn from a finite set of several elements. The dominant approach for doing so is to reduce the single multiclass problem into multiple binary classification problems.[14] Common method for such reduction is building binary classifiers which distinguish between (i) one of the labels and the rest (one-versus-all) or (ii) between every pair of classes (one-versus-one).[15] in this study one-versus-one approach was considered and applied

$$(K_2) = \frac{K!}{(K-2)!*2!} = \frac{K*(K-1)}{2} \quad (13)$$

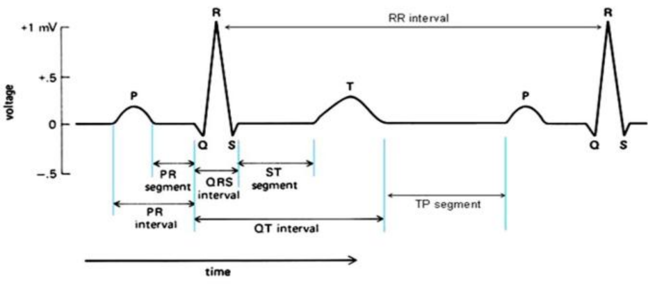

Fig. (2) A Typical ECG Signal

IV. EXPERIMENTAL RESULTS

A. Experimental Dataset

The introduced scheme is implemented in Matlab-command-window, fifteen different records of five rhythms from MIT-BIH arrhythmia database has been used to evaluate the introduced scheme, the chosen recordings were digitized at 360 samples per second per channel with 11-bit resolution over a 10 mV range [18] [tamadur], in particular, the considered ECG-beats refer to the following classes: Normal sinus rhythm denoted as (N),Right Bundle Branch Block denoted as (RBBB), Atrial Premature denoted as(APB), Premature Ventricular Contraction denoted as (PVC), Fusion Beat denoted as (F) and Paced Beat denoted as (P), these classes, which correspond to the following files: 101, 103, 104, 107, 115, 119, 123, 208, 209, 212, 213, 217, 220, 221 and 231.

B. Preprocessing Results

In this stage the designed filters has been implemented and simulated where their frequency response were calculated and plotted fig. [3] and Fig. [4], then the dataset has been used to evaluate these filters fig. [5].

C. Feature extraction

from the captured Daubechies4-coefficients fig. (6) a set of 10-features of ECG-signal are considered; ‘P Q R S T’-peaks are detected and saved over the entire signal and the time interval between two consecutive ‘R’-peaks and other peaks interval are calculated fig. (7). Which will constitute the feature vector that to be fed to the MSVM. The selected elements in the feature-vector were: R-peak amplitude, R-R interval, R-R range, ST segment, T-peak amplitude, P-peak amplitude, QRS interval, QT interval, RS segment, and Signal power.

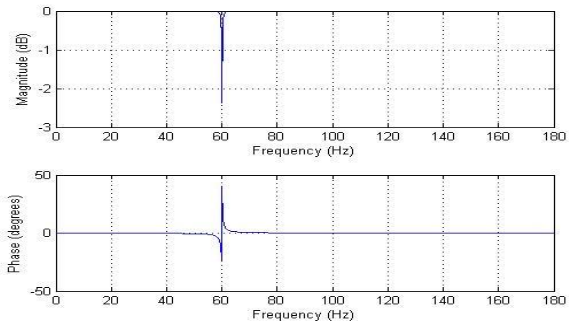

Fig. (3) A 2nd- Order Butterworth Bandstop Filter Frequency-Response

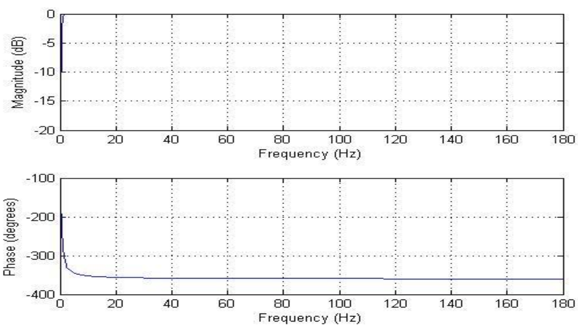

Fig. (4) A 3rd-Order Butterworth High Pass Filter Frequency-Response

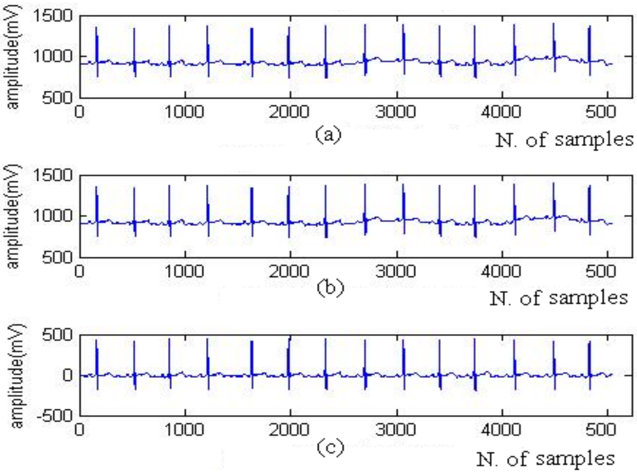

Fig. (5) Removal of Power-Line Interference and Baseline Wander (A) Raw ECG Signal. (B) Power-Line Free ECG Signal (C) Baseline-Free ECG Signal

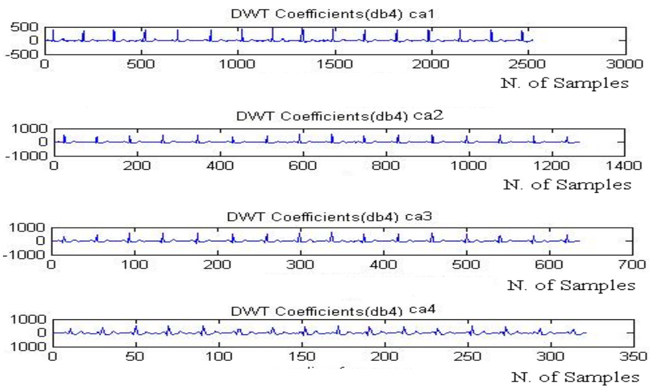

Fig. (6) DWT Coefficients of ECG Level-4 of Record (101)

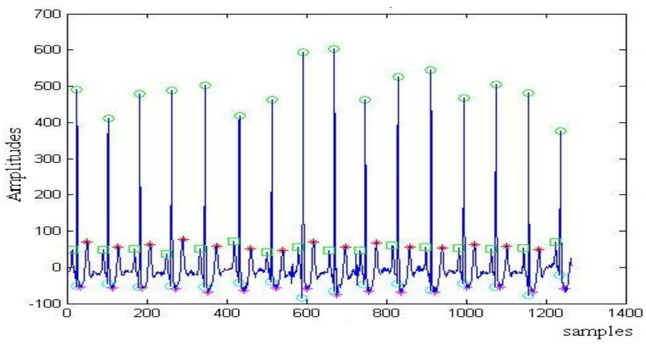

Fig. (7): ECG-Peaks Detection within Record (101)

D. Performance Validation

The classification performance has been evaluated with two measures specific accuracy (sACC) and the overall agreement (accuracy), the experimental results have shown that the proposed system achieves validity as competitive results quality-wise, and the accuracy-rate of classification of Normal sinus Rhythm (N), Bundle Branch Block (RBBB), Atrial Premature Beat (APB), 3Premature Ventricular Contraction (PVC), Fusion Heart Beats (F), and Unclassified Heart Beats (P) were 90.0%, 100%, 66.6%, 100%, 100%, and 100%, respectively, while the

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total accuracy is 93.33%. The following Table(1) lists the of the classification evaluation of the proposed algorithm using specific accuracy (sACC) and the overall agreement (accuracy).

Table (1). Total Accuracy and Specific Accuracy of the Considered Classes and Selected Records

ECG-Beat Class	MIT/BIH Data Record	Specific Accuracy (SACC)
Normal sinus Rhythm (N)	101, 103, 115, 123	90.91%
Bundle Branch Block (RBBB)	212, 231	100%
Atrial Premature Beat (APB)	209, 220	66.67%
Premature Ventricular Contraction (PVC)	119, 208, 221	100%
Fusion Heart Beats (F)	213	100%
Unclassified Heart Beats (P)	101, 107, 217	!00%
Total Accuracy		93.33%

V. CONCLUSION

Advanced mathematical methods and DSP algorithms make possible of development of an intelligent computational systems that could be used for medical applications, in this study a state-of-the-art, reliable arrhythmias detection approach was proposed, implemented, and evaluated. The introduced approach is well defined and justified, in which ten-features of ECG-signal was extracted based-on Daubechies-4, then Multiclass Support-Vector-Machine has been implemented to classify Heart-Arrhythmias. The proposed algorithm was tested and evaluated using MIT-data-base. The implemented algorithms capable of distinguishing six different heart conditions providing very high accuracy that reach 93.333% of overall detection rate.

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