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INTEGRATION OF HRV, WT AND NEURAL NETWORKS FOR ECG ARRHYTHMIAS CLASSIFICATION

A. Dallali, A. Kachouri and M. Samet
Laboratory of Electronic and Technology of Information (LETI)
National School of Engineers of Sfax, BP W 3038, Sfax, Tunisia
Email: dallali_a@voila.fr

ABSTRACT

The classification of the electrocardiogram registration (ECG) into different pathologies disease devises is a complex pattern recognition task. The registered signal can be decomposed into three components, QRS complex, P and T waves. The QRS complex represent the reference for the other ECG parameters; the width and amplitude QRS have more important to identify the ECG pathologies. The statistical analysis of the ECG indicate that they differ significantly between normal and abnormal heart rhythm, then, it can be useful in detection of ECG arrhythmia. The traditional methods of diagnosis and classification present some inconvenient; seen that the precision of credit note one diagnosis exact depends on the cardiologist experience and the rate of concentration. Due to the high mortality rate of heart diseases, early detection and precise discrimination of ECG arrhythmia is essential for the treatment of patients. During the recording of ECG signal, different form of noises can be superimposed in the useful signal. The pre-treatment of ECG imposes the suppression of these perturbation signals, three methods for the noisily of signals are used; temporal, frequency, and time frequency method filter. The features are extracted from wavelet decomposition of ECG signal intensity. The inclusion of Artificial Neural Network (ANN) based on feed forward back propagation with momentum, in the diagnostic and classification of ECG pathologies have very important yield [1, 2]. The four parameters considered for ECG arrhythmia classification are the interval RR, the QRS width, the QRS amplitude, and the frequency of appears QRS. Due to the large amount of input data, needed to the classifier, the parameters are grouped in batches introduced to artificial neural network. The classification accuracy of the ANNs introduced classifier up to 90.5% was achieved, and a 99.5% of sensitivity.

Keywords: cardiac pathologies, ECG, heart rate variability, wavelet transform, ANNs, classification.

INTRODUCTION

In recent years, computer assisted ECG interpretation has played an important role in automatic diagnosis of heart anomalies [1, 3]. The wave forms of ECG; width reflects the physical condition of human heart, is the most biological signal to study and diagnosis cardiac dysfunctions. So, it is important to record the patient's ECG for a long period of time for clinical diagnosis. The clinical significance diagnosis depends on different parameters of ECG; complex QRS, wave P, frequency, Heart Rate Variability R-R. In these applications, it is more important to develop signal processing methods that permit real time feature extraction and de - noising of the ECG characteristic. The extracted parameters are used for the classification of the cardiac pathologies and make an automatic tool of diagnosis in the services of doctors before the arrival of a quantified patient. Many techniques were used for the diagnosis of ECG signal; temporal methods [4, 5], frequency method [4] and time frequency methods [5, 6].

The real time records of ECGs are accompanied by a high frequency signals that superposed with the useful ECG. The suppression of these perturbation signals is necessary to a performance classifier system. The ECG data must be filtered in order to attenuate undesired electrical components of ECG. Over recent years, wavelets transforms play an increasing role in the pre-processing medical signal. The ECG signals are filtered by band pass filters based and discrete wavelet transform.

In the recent years, various algorithms are developed for classification and identification of the ECG anomalies. These algorithms are most based in fuzzy logic and Neural Network techniques. The remaining of the paper is organized as follows: The first stage, point out to the materials and methods used. In this stage, we present the ECG signal and their significant parameters for diagnostic. In the second stage, time and frequency domain are applied to de-noising ECG signal and extract the corresponding features. The extracted features are used to train an ANNs for classification of different anomalies is will be treated in third stage. The simulation results of the neural network classifier will be discussed at the end of the paper.

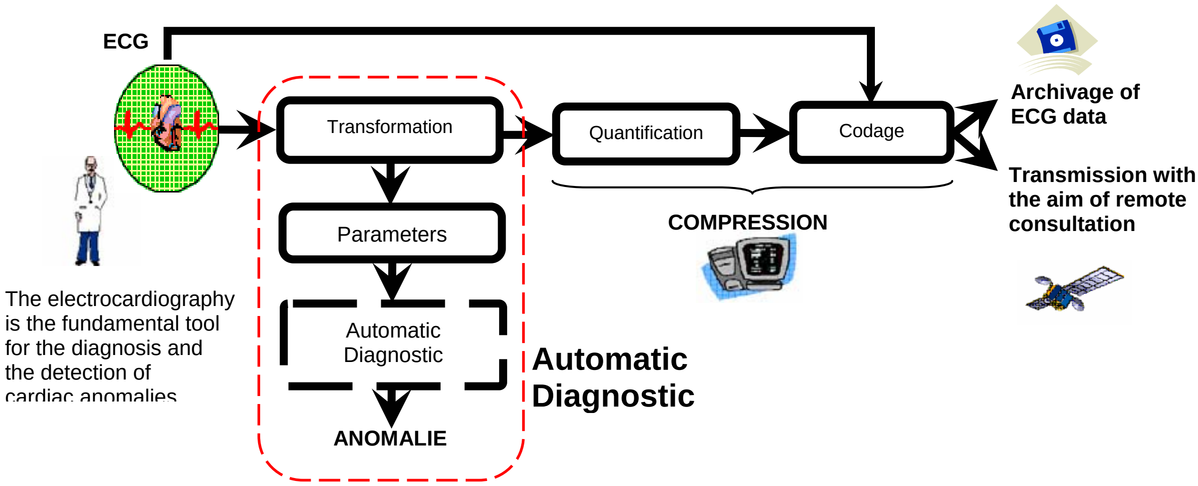

Figure-1. Overview of fully implantable neural recording system using a thermoelectric power.

Characteristics of the ECG

The ECG represents the wave's electrical propagation through the respective regions of the heart (SA. node, Arial Muscle, AV node, Atria ventricular Bundle, Left and Right Bundle Branches). These waves are the major evident observable of the human heart and have been used to intensive diagnosis since of their significance in the context of pathologies [8]. Usually, the listing of the electrical wave's variations on the papers constitutes the ECG signal. Figure-2 shows the temporal characteristics of normal ECG.

Table-1. ECG properties.

Mechanical actions	**Associated wave**	**Duration** (sec)	**Amplitude** (mV)	**Wave frequency** (Hz)	**Axe**
Auricular depolarization	P wave	<0.12	≤ 0.3	10	20° à 80°
Depolarization of the ventricle	QRS Complex	0.08 à 0.12	Q<0 - S>0 R (0.5-2) DI + DII+ DIII > 15	20 - 50	-30° à +110° < -30° axe gauche > 110° axe droit
Repolarization of the ventricles	T wave	0.2	0.2	5	
Repolarization of the auricles	Hidden wave				

The analysis of the ECG morphologic (P wave, QRS wave T wave…) is essential in diagnosis. The Table-1 summarizes the electric properties of a normal ECG. It is know that electrocardiogram signals ECGs are used extensively in different monitoring and diagnostic cardiology applications [9, 10]. So, a Holter monitor produces a large amount of non-stationary and quasi periodic data; example of noise that can be superposed on the useful signal, which are difficult to classify directly the ECG frames. Many methods have been proposed to solve the problem.

REVIEW OF LITERATURE

Sokolow *et al.*, (1990), indicate that the state of cardiac health is generally reflected in the shape of the ECG waveform and heart rate. Cuiwei Li *et al.*, (1995) showed that it is easy with multi scale information / decomposition in wavelets transformation to characterize the ECG waves. Khadra *et al.*, (1997) proposed a classification of life threatening cardiac arrhythmias using wavelet transforms. MG Tsipouras *et al.*, (2004) used time frequency analysis for classification of atrial tachyarrhythmias. Later, Al-Fahoum and Howit (1999) joint radial basis neural networks to wavelet transformation to classify cardiac arrhythmias. Weissan *et al.*, (1990); Akselord *et al.*, (1981); Pomeranz *et al.*, (1985) showed that the spectral analysis is the essential linear techniques used for the HRV signals analysis. Silipo *et al.*, (1998) has shown that the Ann's approach is shown to be capable of dealing with the ambiguous nature of the ECG signal when tested and compared with the most common traditional ECG analysis on appropriate data bases [11]. Ali Shahidi Zandi *et al.*, (2005) used a method based on the continuous Wavelet transform and Artificial Neural Network for detection of ventricular late potentials in High-Resolution ECG signals. Mei Jiang Kong *et al.*, (2005) used block-based neural networks to classify ECG Signals. Fira *et al.*, (2008) proposed an ECG compressed technique and its validation using NN's. The choice of the wavelet family as well as the selection of the analyzing

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function and level decomposition into these families have been discussed to the Daubechies decompositions provided by the Daubechies wavelet (level 3), the coiflet wavelet (level 6) and the symetric wavelet (level 6) [12].

In the present work, heart rate variability is used as the base signal for classification of cardiac abnormalities into three classes. Four parameters extracted from the cardiac signals are used for the proposed classification.

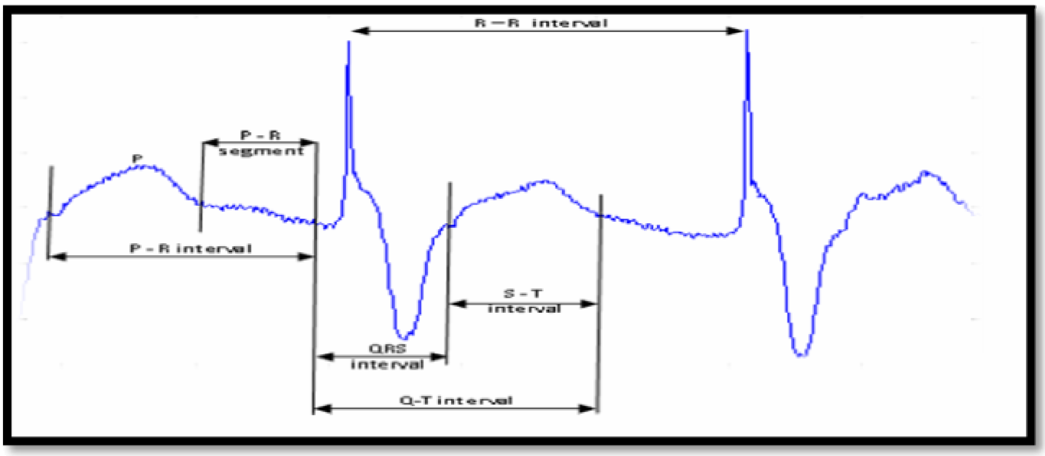

Figure-2. Temporal characteristics of normal ECG.

MATERIALS AND METHODS

ECG database

The ECG recording from MIT_BIH arrhythmia database was studied. Each recording has duration of 30 minutes and includes two leads. The sampling frequency is 360 Hz and the resolution is 1200 samples per 1 mV.

Processing

ECG signals can be contaminated with several kinds of noise, such as power line interference (A/C), baseline wandering (BW), and electromyographic noise (EMG), which can affect the extraction of parameters. The processing of the ECG recorded signal was consistent the suppression of these perturbation signals; the high frequency noise and the low frequency drift.

- Low and high pass filter for drift, high frequency and line base suppression.
- Time frequency methods, based on the Discrete Wavelet Transform (DWT) and thresholding coefficients [13, 14] are applied to de-noising ECG signals; the algorithm for de-noising ECG by DWT is to decompose the signal in approximation and details coefficients.

$$W_{ECG}(2^j,b) = \int_{-\infty}^{+\infty} ECG(t).\Psi^*_{2^j,b}(t).dt \qquad (1)$$

with

$$\Psi_{2^j,b}(t) = \frac{1}{2^{j/2}}.\Psi\left(\frac{t-b}{2^j}\right) = \frac{1}{2^{j/2}}.\Psi\left(\frac{t}{2^j}-n\right) \qquad (2)$$

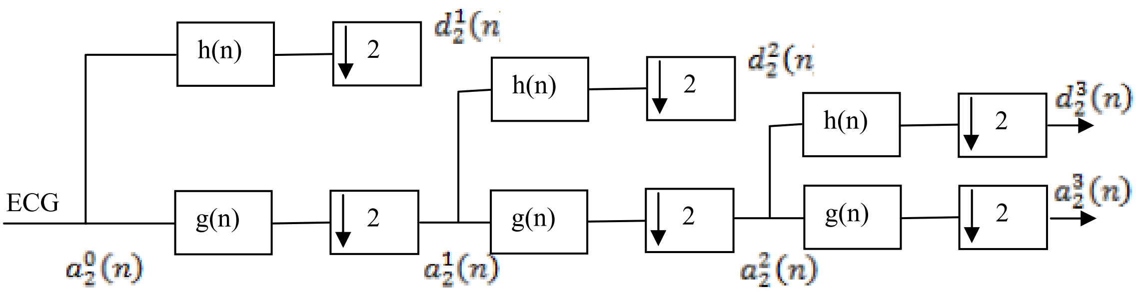

Figure-3. Multi-resolution analysis: decomposition of ECG signal.

Parameters detection

The first feature extracted from the ECG recorded is the R wave. Initially, a point in the QRS complex is detected (max of QRS). Then, the wave of the QRS complex (R wave) is identified in the window [R_wave - 280 ms, R wave + 120 ms]. A wave P detection, using the algorithm proposed by Pan and Tompkins [15]. The RR-interval signal is constructed by measuring the time

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ARPN Journal of Engineering and Applied Sciences

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interval between successive R waves. The frequency of the ECG signal of a normal subject is approximately 60 Hz and can go up 130 Hz for an abnormal patient. The block diagram of the proposed method for ECG beat classification is depicted in Figure-4. The method is divided into three steps: (1) prepossessing (2) extraction of parameters and (3) classification by ANNs.

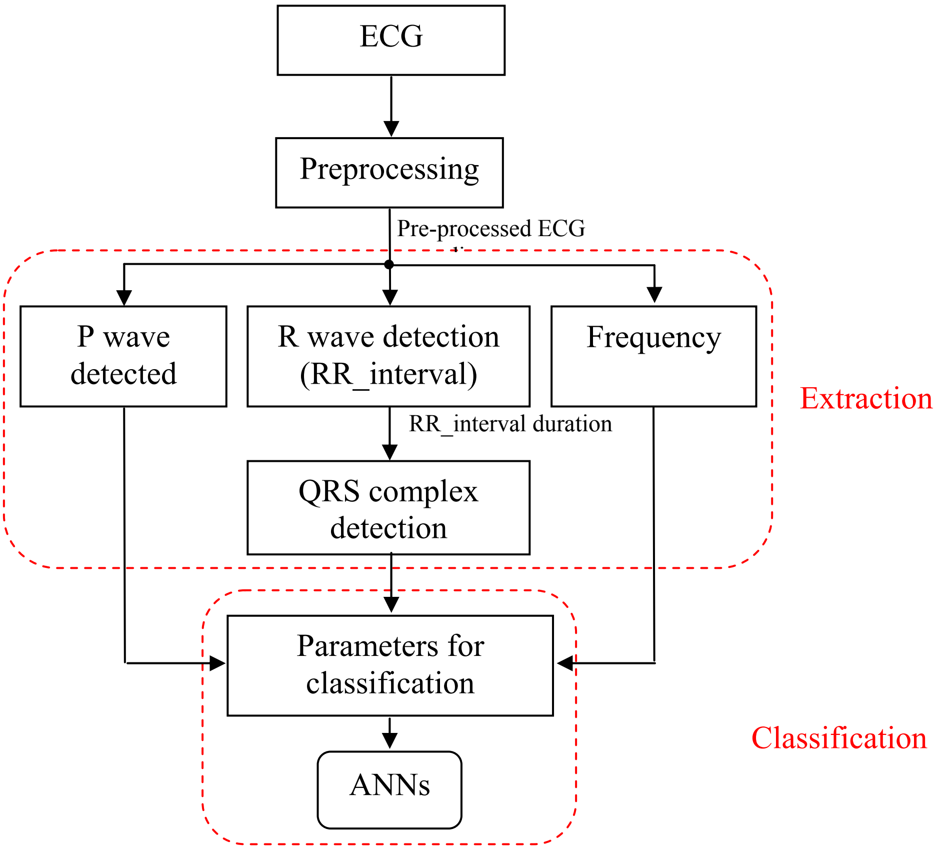

Figure-4. Block diagram of the proposed scheme for ECG parameters extraction and classification.

FILTERING OF THE ECGs SIGNALS

Monitoring of the electrocardiogram signal during normal activity using Holter devices has become standard of cardiac arrhythmias. The most important problems in real _ time ECG recording are [12, 13]:

- Muscle noise
- Power line interference (50 or 60 Hz noise induced by lines)
- Base line wander (a very low frequency change of iso-electric level of ECG)
- Artifacts due to electric motion
- Physiological variability of QRS complex

The pre-treatment of ECG signals imposes the extraction of the useful ECG signal from noisily ECG signal.

Temporal filtration

The temporal methods of filtration are based on low and high pass filters in cascade.

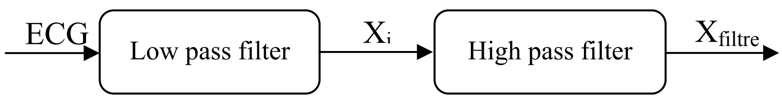

Figure-5. Cascade temporal filter.

There are many power spectrum features were extracted from the ECG signal at frequency interval (4 to 30 Hz), shown in Figure-6. The term power spectrum means the amount of power per unit of frequency as a function of the frequency.

VOL. 6, NO. 5, MAY 2011 ISSN 1819-6608
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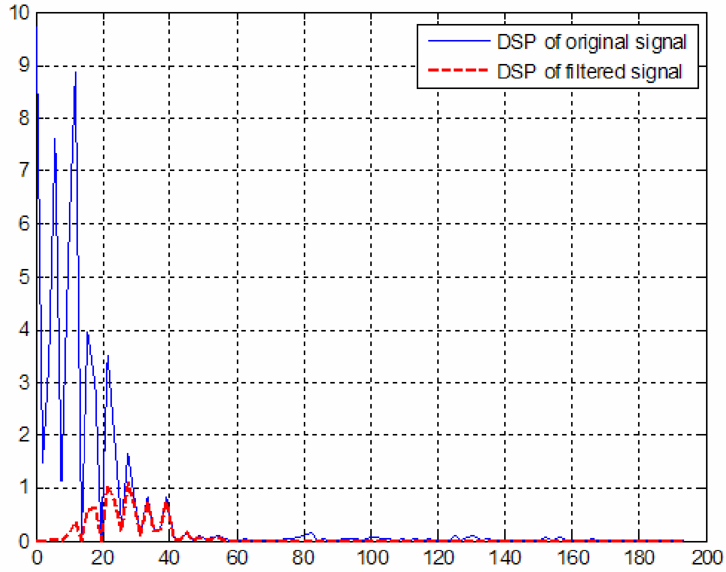
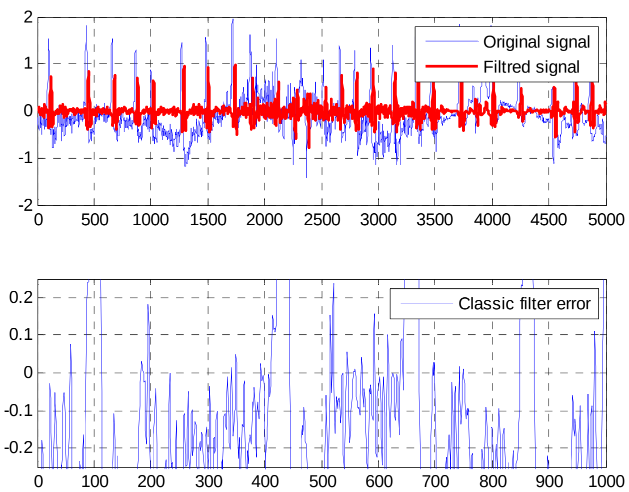


Figure-6. Power spectral density of signal MIT_203 (a) original signal (b) filtered signal.

Time frequency filtered

For many years now, wavelets have proved their efficiency in various applications. Signal processing is performed using the wavelet equivalent filters. The multi-scale feature of wavelet transform is applied to distingue the noise, baseline drift and artifacts. The choice of wavelet family as well as the selection of the function analyzed. Daubechies wavelet family presents the similar shape of the QRS complex and their energy spectrums are focalized around low frequencies. In this work, Daubechies wavelet at level three'db3' is used. We set the threshold $\lambda_i = 0.76\%$, this value is fixed for all the earlier analysis with the wavelet function. The wavelet transform algorithm adopted for de-noising the ECG recorded is based to decompose the signal ECG in approximations and details coefficients [15]. Figure-7 illustrates the filtration of the ECG record MIT_203 using wavelet transform and temporal classic filter. It is noticed that the line base is obtained and the high frequency noise is eliminated.



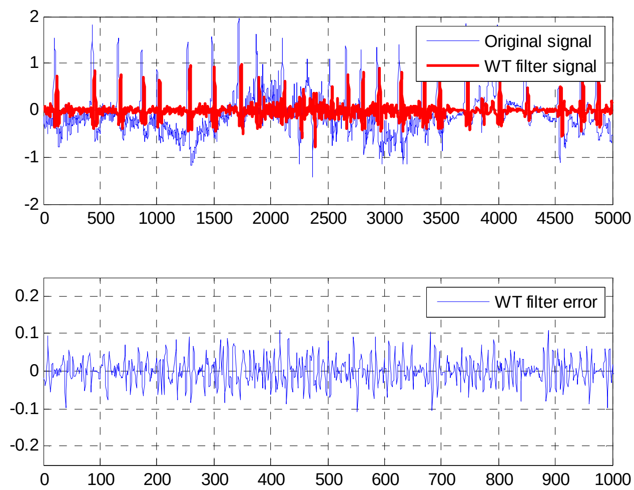


Figure-7. Signal ECG of MIT 203 presenting a deviated line base (a) original signal filtered signal by classic filter (b) original signal filtered by wavelet transform filter.

NON LINEAR ANALYSIS

The cardiovascular system is too complex to be linear, and treating it as a non-linear system can lead to better understanding of the system dynamics. To study this system, we utilized nonlinear parameters as follows:

SD1/SD2

Poincare plot is a graphical representation of the correlation between successive RR intervals. The Poincare plot may be analyzed quantitatively by calculating the standard deviation of the distances of the RR (j) to the line $y = x$ and $y = -x + 2 * mean(RR(j))$. The standard deviation are referred respectively to; the fast beat-to-beat variability of RR (j), and the description of the longer-term variability of (RR (j). The ratio SD1/SD2 is to describe the relation between these components.

VOL. 6, NO. 5, MAY 2011 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

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DFA

The Detrended Fluctuation Analysis (DFA) is used to quantify the fractal scaling properties of short interval R-R interval signals. This technique is a modification of the root-mean-square analysis of random walks applied to non stationary signals [16]. The root-mean-square fluctuation of an integrated and detrended time series is measured at different observation windows and plotted against the size of the observation window on a log-log scale. The root-mean-square fluctuation of this integrated and detrended series is calculated using the equation:

$$F(n) = \sqrt{\frac{1}{N} \cdot \sum_{j=1}^{N} [y(j) - y_n(j)]^2} \qquad (3)$$

Spectral entropy

Spectral entropy quantifies the spectral complexity of the time series. Application of Shannon's channel entropy gives an estimate of the spectral entropy of the process, where entropy is given by:

$$H = \Sigma_f \, p_f \cdot log\left({}^{1}/_{p_f}\right) \qquad (4)$$

Where pf is the PDF value at frequency f. The spectral entropy H (0 <H <1) describes the complexity of the HRV signal. This spectral entropy H was computed for the various types of cardiac signal.

ARTIFICIAL NEURAL NETWORK (ANN) CLASSIFIER

The Artificial Neural Network (ANN) is has to be applied, the structure of discreet propagation "feed forward" is used in the training stage of the ANNs. In this paper, we are interested in the classification of the arrhythmias presenting some anomalies. All the ECG data, used from the MIT-BIH Arrhythmia Database which was digitized at a sampling rate of 360 Hz [17].

Artificial Neural Network is biologically inspired network that are suitable for classification of biomedical data. A combination of wavelets transform and ANNs is proposed to classify cardiac arrhythmias [18-24]. The precision of classification results of the anomalies depends on the number of parameters selected; the number of neurons of input layer is equals to the numbers of parameters used for classification. The parameters extracted are used to train the ANNs. Typically, for classification, the configuration usually used are multilayer feed forward neural networks with Log-sigmoid activation function that using the generalized back propagation for training which minimize the squared error between the desired outputs and the actual outputs of the ANNs. The desired output is being a real number in the interval (0 – 1).

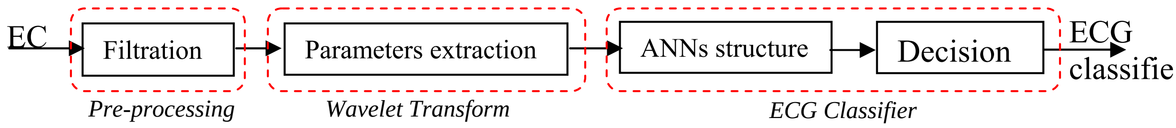

Figure-8. Classification of ECG by artificial neural networks.

A dynamical analysis of heart rate behaviour derived from non-linear mathematics can reveal abnormal patterns of RR interval dynamics which cannot be detected by commonly employed moment statistics of heart rate variability. The HRV signal can be used as a reliable indicator of heart diseases (Figure-9).

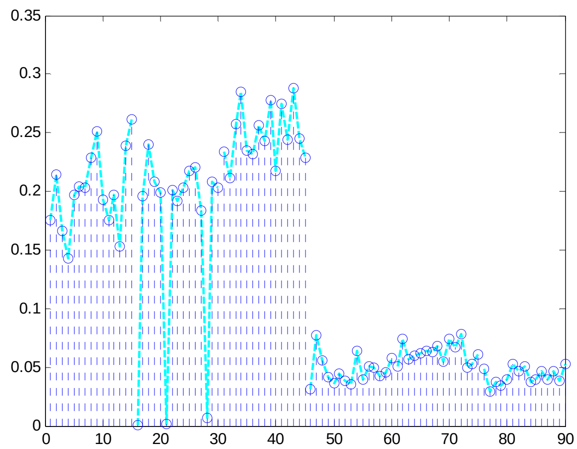

Figure-9. R peak detection of ECG records used for classification.

The classification steps of the signals are depicted in Figure-8. One distinguishes the stage of filtering, the stage of extraction of the parameters and the stage of neuronal classification (training and validation of the method). The architecture of the ANN contains: four inputs neurons, two hidden layer with eight neurons and one output neurons Figure-10. The training of the artificial neural network ends if the sum of the square errors for all segments is less than 0.01. The number of data set used for training and testing of the ANNs classifier and the results obtained are tabulated in Table-2. The parameters extracted (P-wave, HRV, QRS and, Frequency), are used as inputs vector to ANNs classification. The output of the classifier is a graphical representation Figure-11.

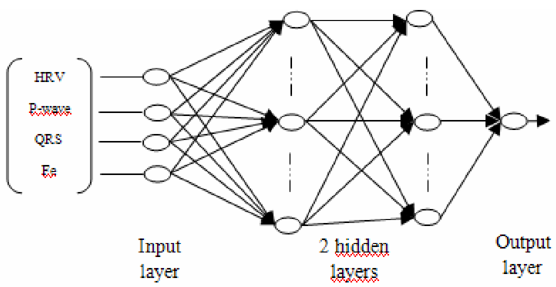

Figure-10. Three layer feed forward neural network.

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SIMULATION AND RESULTS

To evaluate the performance of classifier; three criteria are used that defined below:

$$Sensitiviy(\%) = \frac{TP}{TP + FN} \cdot 100 \qquad (5)$$

$$Specifity(\%) = \frac{TN}{TN + FP} \cdot 100 \qquad (6)$$

$$Accuracy(\%) = \frac{TP + TN}{TP + TN + FN + FP} \cdot 100 \qquad (7)$$

$$FDR(\%) = \frac{FP + FN}{TP + TN + FN + FP + U} \cdot 100 \qquad (8)$$

$$Entropy(P) = -\frac{P}{N} \cdot log_2\left(\frac{P}{N}\right) - \frac{n}{N} \cdot log_2\left(\frac{n}{N}\right) \qquad (9)$$

The results of classification using the partition neuronal classifier are summarized in Table-2. In this case, the accuracy and sensitivity are higher and the rate of false classification is weaker than total signal classified (6.2%).

The performance of the combination between wavelet transform and neural network for classification are considered to be acceptable comparatively with the manual diagnostic. These approaches can constituent a tool for the diagnostic and the classification of the normal and abnormal cardiac signal. The three types of ECG signals are normal signal ECG (Norm), Left bundle branch block beat (Lbbb) and, Right bundle branch block beat (Rbbb). For training the neural network a back-propagation algorithm with gradient descent and cross-validation was used.

The patterns used in the three sets above were distinct. The records no. 100, 101,104, 105, 106, 107, 108, 109, 111, 112, 113, 203, 207, 212, 214, 231 were used for training, testing and validation. The error function used was the mean square error and the stop criterion was the least error for the validation set. The ANN algorithm has the advantage of not requiring information on the class statistics; it can be easily implemented and has a small probability of error.

Table-2. Classification of cardiac arrhythmia using ANNs.

Class	Data sets testing	Sets correctly classified	Sets misclassified	Accuracy (%)	Sensitivity (%)	Entropy (%)
1 Norm	60	57	3	95.00	100	92.80
2 Lbbb	35	33	2	94.28	100	87.49
3 Rbbb	20	18	2	90.00	95.24	76.14
Total	**129**	**121**	**93.79**	**93.03**	**96.94**	**71.09**

As well as the previously, we extracted characteristic parameters of the ECG signals for various pathologies. These decomposition parameters constitute a data base for the learning ANNs. The back-propagation neural network (BPNN) used in this study is a three-layer feed-forward structure. In order to overcome the difficulty of intensive computational time taken using ANNs classifier, attempt has been made to reduce the numbers of input data parameters using WT which is beneficial for ECG decomposition. The objective of using WT is to increase the numbers of points of ECG and extract the significant parameters for automatic and fast ECG beat classification

DISCUSSION AND CONCLUSIONS

The HRV signal, frequency, P and QRS waves can be used as reliable indicators of heart diseases. In this paper, both Wavelet Transform and Neural Network classifier are presented as diagnostic tools to aid the physician in the analysis of heart diseases. Three types of ECG samples were selected from MIT - BIH arrhythmia database for experiments. The aim of using Artificial Neural Networks (ANN) is to decrease the error by grouping similar parameters training data. The features of obtained training parameters are extracted using wavelet transform (WT). The ANN - WT has been presented and developed to classify electrocardiography signals. Further it is observed that the % error is also less (Figure-11). The technique used is obtained by incorporating the ANNs, Wavelet transform and significant parameters; extracted from the ECG records such as: Heart Rate Variability (HRV, P-wave, QRS, Frequency), combining their advantages. The analysis of the results listed in Table-2 show it is evident that the classifiers presented are effective for classification of cardiac arrhythmia with an overall accuracy of 93.03%. The accuracy of the tools depends on several factors, such as the size of database and the quality of the training set and, the parameters chosen to represent the input vector of the classifier. The single output neuron, allowing to easily classification according the abnormalities ECG signal, is used. In bottom, the error curve illustrates the smallest values obtained (less than 2%). The results conclude that it is possible to classify the cardiac arrhythmia with the help of neural networks. The advantage of the ANNs classifier is its simplicity and ease of implementation.

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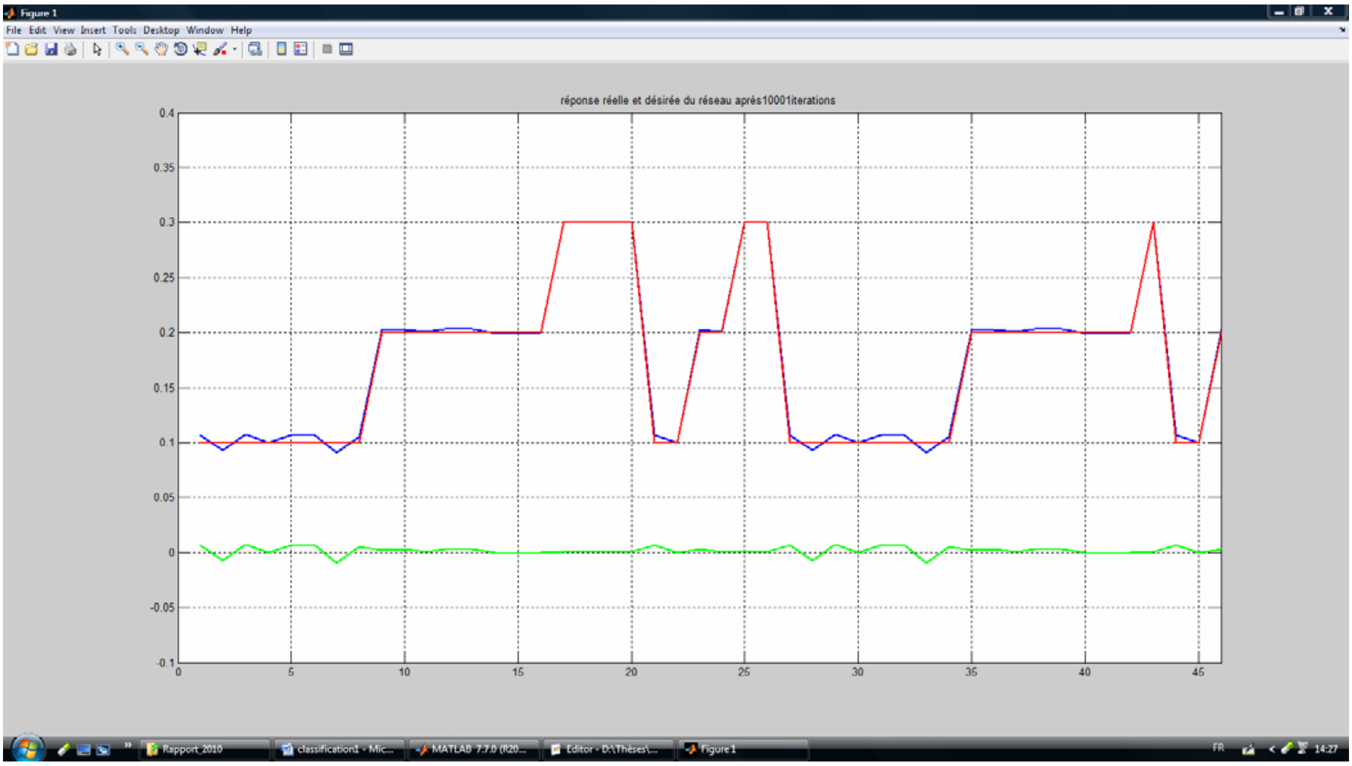

Figure-11. The output of ANNs classifiers.

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