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

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### 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.

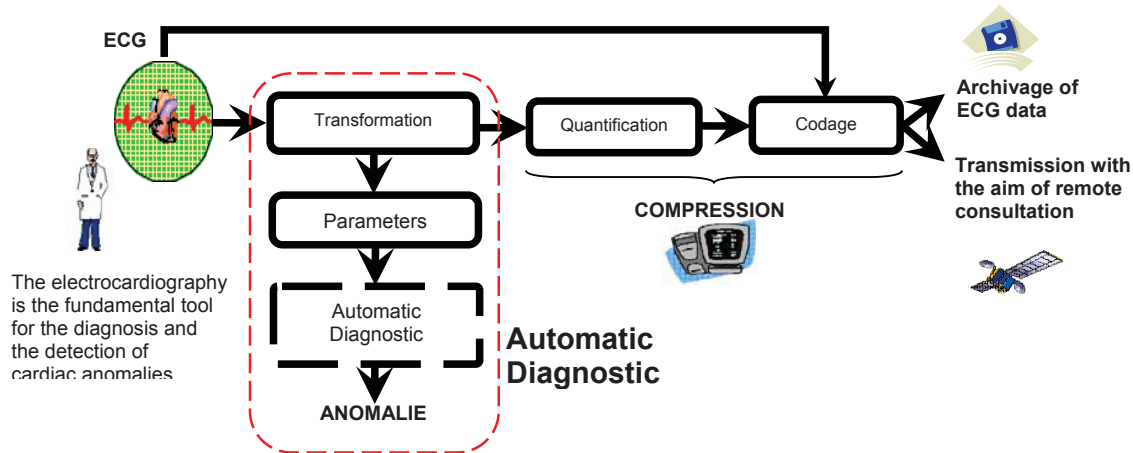


Figure-1. Overview of fully implantable neural recording system using a thermoelectric power.

### Characteristics of the ECG

The ECG represents the wave's electrical propagation through the respective regions of the heart (SA. node, Atrial 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	$\leq 0.3$	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 known 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



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 symmetric 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.

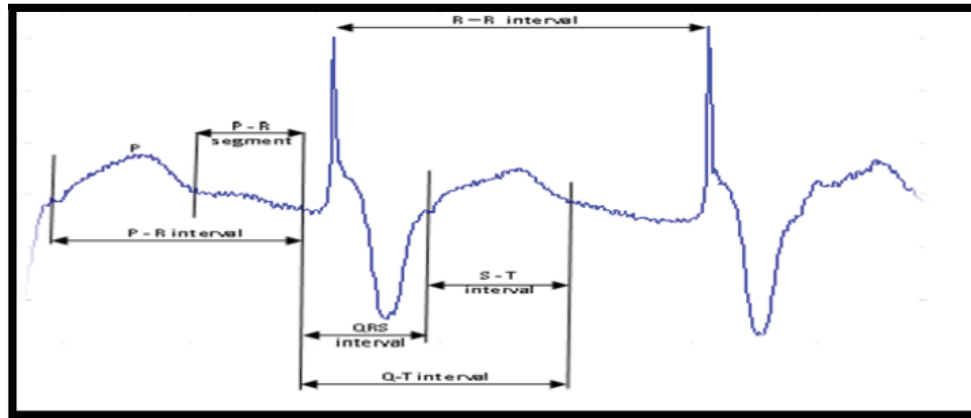


Figure-2. Temporal characteristics of normal ECG.

## 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.

$$W_{ECG}(2^j, b) = \int_{-\infty}^{+\infty} ECG(t) \cdot \Psi_{2^j, b}^*(t) \cdot dt \quad (1)$$

with

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

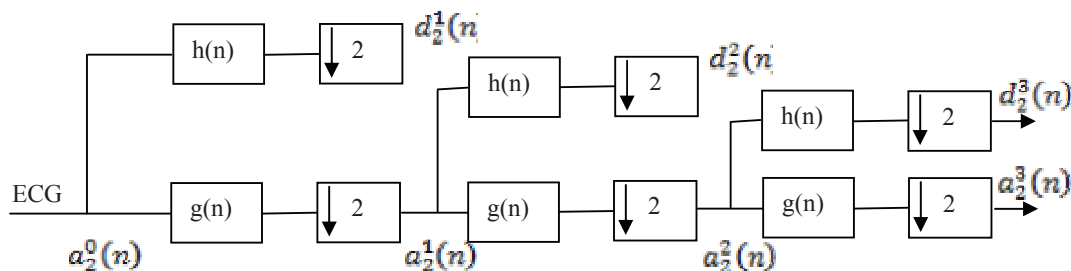


Figure-3. Multi-resolution analysis: decomposition of ECG signal.

### Parameters detection

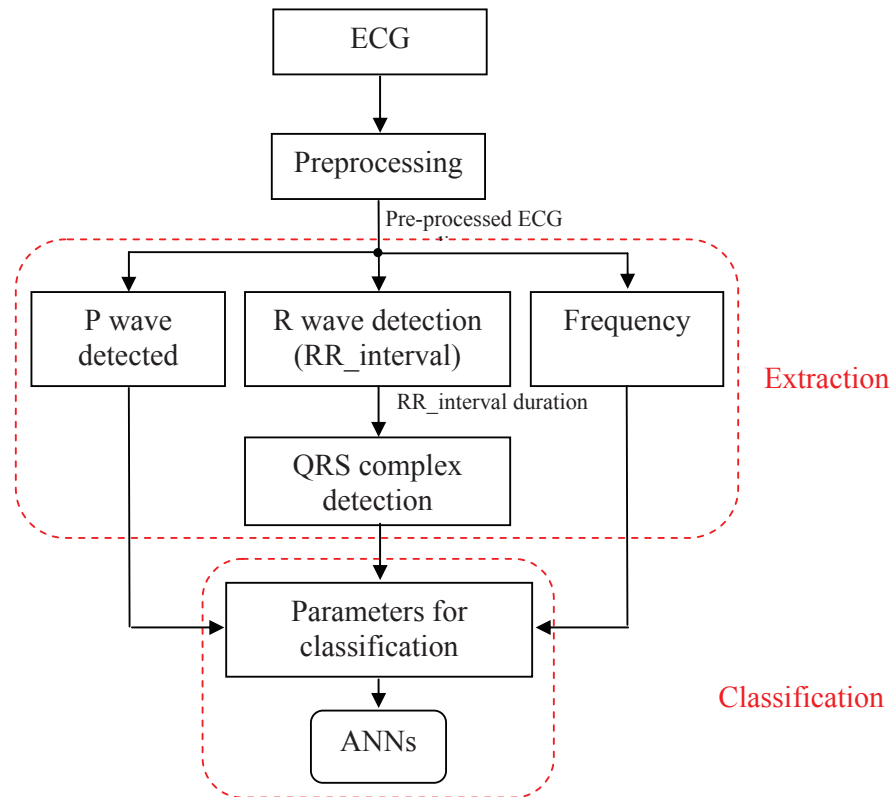
The first feature extracted from the ECG recorded is the R wave. Initially, a point in the QRS complex is detected (max of QRS). Then, the wave of the QRS

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



interval between successive R waves. The frequency of the ECG signal of a normal subject is approximately 60 Hz and can go up to 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) preprocessing (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]:

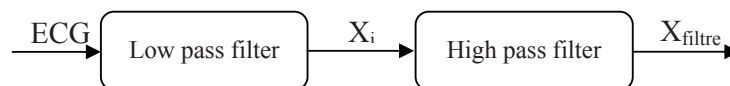
- Muscle noise
- Power line interference (50 or 60 Hz noise induced by lines)
- Base line wander (a very low frequency change of iso-electric level of ECG)

- 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.

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