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# Wavelet Transformation and Wavelet Network Classifier for ECG Classification

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**Abstract:** The Electro Cardio Gram ECG signal is a highly used examination in the field of cardiology these pathologies are generally reflected by disorders of the electrical activity of the heart. In this study, we have addressed the problem of automatic recognition of heart beats through the development and implementation of a method combining wavelet transform with neural networks. This method consists denoising, extraction and classification models for robust automated ECG analysis. For the classification module a hybrid network combining neural networks and wavelets has been proposed, implemented and evaluated for identification of the ECG classes. This technique is based on the use of wavelet functions as activation functions in neural networks which allowed the wavelet network to have a better adaptability and flexibility during the learning process given the parameters of translation and expansion of the functions of wavelets. Indeed, theevaluation of the results obtained by the implemented wavelet network are satisfactory with respect to other neural networks in terms of the rate of classification of the heart beats. The association of neural networks with the wavelet functions made it possible to extract the strengths of the two techniques (the learning capacity of the neural models and the multi resolution analysis of the wavelets). The results obtained showed that the proposed method can be considered as an effective method for classification of cardiac arrhythmias with a very acceptable accuracy of more than 98.78%.

**Key words:** ECG, neural, network, wavelet, network, results

## INTRODUCTION

Cardiovascular disease is the most common cause of death world wide, according to annual statistical studies conducted at the World Health Organization (WHO) level (Lloyd-Jones *et al*., 2010). Therefore, the diagnosis of these dangerous diseases seems a vital task. In cardiac services at the hospital level, the Electro Cardio Gram (ECG) signal is still one of the predominant and widely used tools for the diagnosis and analysis of cardiac arrhythmias.

In reality, the ECG examination is a non-invasive tool performed by the physician in order to explore the functioning of the heart by the use of external electrodes placed in contact with the skin. This is a signal that reflects the electrical activity of the heart.

From the ECG signal, some important parameters can be extracted. In general, the durations and forms of the different waves are considered as indicative signs of certain cardiac abnormalities. However, manual detection of waveforms characteristic of the ECG signal and the classification of heartbeat are difficult and annoying tasks, especially for the analysis of long-term recordings as in the holter examination (Oresko *et al*., 2010).

As a result, automatic ECG signal analysis systems capable of assisting physicians in diagnosis appear to be necessary because of the large number of patients in intensive care units and the need for continuous observation. Several automatic systems have been developed to aid cardiac diagnosis through the ECG signal. These systems should be easily applicable, scalable, accurate, robust and stable (Nikus *et al*., 2010).

Generally, these methods are developed in two main stages the characterization of the ECG signal and the classification module.

The first step in the characterization of the ECG can be evaluated in the temporal domain in order to obtain morphological characteristics (such as the width, height and surface of the QRS complex, variability of the heart rhythm, etc.) (Bortolan *et al*., 1996; Chazal *et al*., 2004) or in the frequency domain in order to find changes in power spectra of the QRS complex between normal and abnormal beats (Minami *et al*., 1999; Ji and Zhu, 2003).

Moreover, the time-frequency analysis (Dickhaus and Heinrich, 1996; Lin *et al*., 2008) makes it possible to take advantage simultaneously of the temporal and frequency

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characteristics of the ECG signal. Similarly, spatial treatment of ECG has often been used to analyze the non-linear behaviour of HRV (Wang *et al*., 2001; Lin, 2006) cardiac variability. For the second step concerning classification, several techniques have been developed such as Artificial Neural Networks (ANN) which are used according to different architectures such as (KSOM) (Mazel and Hayes, 1992; Vines and Hayes, 1993), Multi Layer Perceptron (MLP) (Barnsley, 2014) and Probabilistic Neural Networks (PNN) (Lin and Wang, 2006).

The classification of cardiac signals is considered as a medical decision-making aid it encompasses several disciplines such as artificial intelligence, signal processing, software and knowledge engineering and in addition the medical aspect.

Automated method for heart classifier is proposed based on a combination of artificial neural networks with the wavelet transform.

The wavelets were used both for the characterization of the ECG signal and also combined with the neural networks for the classification of the heart beats. Five different types of beats are chosen: normal beats (N, Normal) Premature Ventricular Contraction (PVC) Left Bundle Branch Block (LBBB) Right Bundle Branch Block (RBBB) and premature A trial Premature Contraction (APC) to evaluate the proposed solution.

The QRS complex it is a set of positive and negative deflections that correspond to the contraction of the ventricles. For a normal case, it has a duration of <0.12 sec and its variable amplitude is between 5 and 20 mV.

## MATERIALS AND METHODS

**Artificial intelligence and ECG:** The application of Artificial Intelligence (AI) methods on the ECG signal has become a very important trend for the recognition and classification of different types of cardiac arrhythmias. Thus, many solutions have been proposed for the development of automated systems for the analysis, recognition and classification of the ECG.

Often we find several techniques in the literature that apply the approaches of artificial intelligence (Gang *et al*., 2000) and more particularly the networks of artificial neurons for the automatic analysis of ECG Electro Cardio Gram signal.

Wankhede (2014) shows that neural networking techniques and more specifically, MLPs and Self Organizing Maps (SOMs) can be used for the classification of the ECG signal.

Partu and Khamiss (2009) used the Multi-channel Adaptive Resonance Theory (MART) network to classify ECG signals. The implementation of the results obtained shows that this classifier can discriminate the beats of the normal 'N' type of the ventricular beats 'V' with good accuracy.

Alan and nikola by Jovic and Bogunovic (2007) described the theory of chaos applied to the extraction of ECG characteristics. Several chaos methods including phase and correlation dimension space, spatial filling index, central trend measurement and approximate entropy are explained in detail. A new environment extraction feature called "ECG chaos extractor" was created in order to apply these chaos methods for the recognition of different types of arrhythmias.

Other approaches such as the bayesian and heuristic approach (Gao *et al*., 2005; Wiggins *et al*., 2008) and markov models (Samar *et al*., 2011; Liang *et al*., 2014) have also been tested for the classification of ECG signals. Several studies have shown and confirmed the performance of neural networks for the detection and recognition of abnormalities in an ECG signal. The use of neural networks for ECG signal analysis offers several advantages over other techniques. Neural networks have benefited from their statistical characteristics to be considered a very interesting tool for the analysis of the ECG given the non-linear and chaotic nature of the ECG. For this reason in most cases, neural networks are often present in the hybrid techniques of artificial intelligence which combine several methods in a single method in order to take full advantage of their advantages. In the following, we will study the different fields of application of methods based on artificial neural networks in the discrimination and classification of cardiac pathologies based on the processing of ECG signals and more particularly the wavelet networks which combine the neural networks with the wavelet functions.

**QRS detection of the ECG signal by wavelets:** As with most forms recognition applications, the characterization step is necessary for the automatic recognition of heartbeats. This characterization step is essential for the rest of the researcher because it will above all make it possible to extract the useful information in the ECG signal and to make it easily exploitable, either by clinicians or by automatic data processing algorithms (Zidelmal *et al*., 2012).

This information corresponds to the indicators used by cardiologists to characterize the cardiac cycle in particular the intervals and amplitudes of the waves constituting the ECG signal as well as the heart rate.

For a clinician this information extraction is carried out each time a patient's ECG signal is analyzed. Its

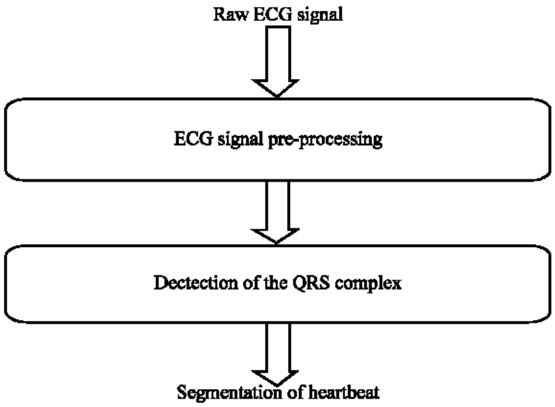


Fig. 1: Steps of the segmentation of the ECG signal

automation is however, very important in the face of the large amount of data which will save time as well as a better ability to perform several analyzes.

In this research, the characterization of the complex QRS of each cardiac beat in order to extract the necessary parameters which will then allow to recognize well the normal beats and the pathological beats. This operation should be as efficient as possible because it reduces the size of the data and retains information that can be interpreted by specialists. It is carried out in two main stages:

- A first pre-processing step whose role is to eliminate artifacts that would hamper the correct segmentation of the beats (Strasser *et al*., 2012)
- And a second stage of detection of the QRS complexes by the localization of the R peaks in the ECG signals (Joshi *et al*., 2013)

In general, the characterization operation of the ECG signal can be broken down into 2 steps illustrated in Fig. 1.

**ECG signal pre-processing:** The different noises that stain an ECG signal are considered undesirable and can alter more or less the clinical information. In addition, the difficulties in detecting QRS complexes reside essentially in the great variability of the signal shape and the presence in the ECG of these unnecessary noises of various origins. It is therefore, important to know what types of noise can contaminate an (ECG) Electro Cardio Gram signal.

**Types of noise present in the ECG signal:** During the acquisition of the ECG signal, undesirable events called artifacts may appear on the electrocardiographic tracing. The problem is often posed during automatic signal processing where the presence of these noises can lead to errors in the diagnosis. These noises can be categorized according to their origins into two broad categories, technical noises and physical noises (Joshi *et al*., 2013).

**Technical noises:** Technical noises are noises caused by the material used during recording.

**Physical noise:** Physical noises are artefacts generated by either the electrical activities of the human body such as muscular contractions or movements during breathing.

**Signal pre-processing:** Details coefficients is responsible for unwanted oscillations in the ECG signal. Thus two techniques of selection of detail coefficients based on a threshold value are introduced by Donoho and Johnstone (1995). These techniques are known as soft thresholding and hard thresholding (Behar *et al*., 2013).

Assume $\{\beta_{jk}, k\in Z\}$ are detail coefficients of the noisy signal. In the hard thresholding one replaces $\beta_{jk}$ with $\beta_{jk}$ defined by:

$$\hat{\beta}_{Jk} = \begin{cases} \beta_{Jk}, \text{ if} \left|\beta_{Jk}\right| \geq T_r \\ 0, \text{ if} \left|\beta_{Jk}\right| < T_r \end{cases} \tag{1}$$

where, $T_r$ is a certain threshold. In the soft thresholding one replaces with defined by:

$$\hat{\beta}_{Jk} = \begin{cases} \text{sign}\left(\beta_{jk}\right)\left(|\,\beta_{jk}\,| - T_r\right), & \text{if} \mid \beta_{jk} \mid \geq T_r \\ & \text{if} \mid \beta_{jk} \mid < T_r \end{cases} \tag{2}$$

where, the value of the threshold $T_r$ is based on some prior information that may exist on the signal. A fixed threshold $T_r$ is introduced by Donoho and Johnstone (1995) in the form:

$$T_r = \sigma\sqrt{2\log(n)} \tag{3}$$

Where:

$\sigma$ = Estimated using the median of the absolute deviation of the detail coefficients of the first wavelet decomposition of the signal
n = Number

$$\sigma = 1.483\times\text{median}\left[\left(\beta_{j-1,k}\right)k \in Z\right]$$

Let J be the highest resolution level of the signal. Steps of high frequency noise cancellation using soft thresholding are do the first decomposition of the ECG signal x (t):

$$x(t) = \sum\nolimits_{k=0}^{2J-1} \alpha_{Jk}\phi_{Jk}(t) \tag{4}$$

First decomposition of x (t) gives:

$$x(t) = \sum_{k=0}^{2^{J-1}-1} \alpha_{J-1,k}\phi_{J-1,k}(t)+\sum_{k=0}^{2^{J-1}-1} \beta_{J-1,k}\psi_{J-1,k}(t) \quad (5)$$

Compute σ from $\beta_{j-1k}$, k∈Z and $T_r$ fromequation (3). Compute the complete discrete wavelet decomposition of the signal. The expression of x(t) becomes:

$$x(t)=\alpha_{00}\phi_{00}(t)+\sum_{j=0}^{J}\sum_{k=0}^{2j-1}\beta_{jk}\psi_{jk}(t) \quad (6)$$

Replace all the detail coefficients with Eq. 2. We obtain the new signal x(t):

$$\hat{x}(t)=\alpha_{00}\phi_{00}(t)+\sum_{j=0}^{J}\sum_{k=0}^{2j-1}\hat{\beta}_{jk}\psi_{jk}(t) \quad (7)$$

Compute the inverse discrete wavelet transform of x(t) to obtain the denoised signal corresponding to the original signal x(t):

$$\hat{x}=\sum_{k=0}^{2^j-1}\hat{a}_{Jk}\phi_{Jk}(t) \quad (8)$$

**Detection of the QRS complex:** To perform an automatic analysis of the ECG signal, detection of QRS complexes is a very important step. The detection of QRS complexes can be accomplished by a simple thresholding of the signal since the R waves are generally larger than the other waves in terms of amplitudes. But sometimes in some cases, the amplitude of the T wave is comparable to that of the R wave which could induce one of the errors in the end result of detection.

Moreover, the R wave may sometimes have a small amplitude and a very variable morphology from one cardiac cycle to another. Thus, good detection of QRS complexes is essential. This therefore requires a very adequate signal processing due to the difficulties encountered.

**Principle of the QRS complex detection algorithm:** The evolution of the power of digital processing tools led to the design and implementation of a variety of algorithms dedicated to the automatic detection of QRS complexes (Behbahani and Dabanloo, 2011).

Thus, the detection of the QRS complex has been the subject of much research and continues to be a highly developed field of research. The method proposed for the delineation of QRS complexes is based on a multi-resolution analysis by the wavelet transform, the general diagram of the different steps of the developed algorithm is illustrated in Fig. 2.

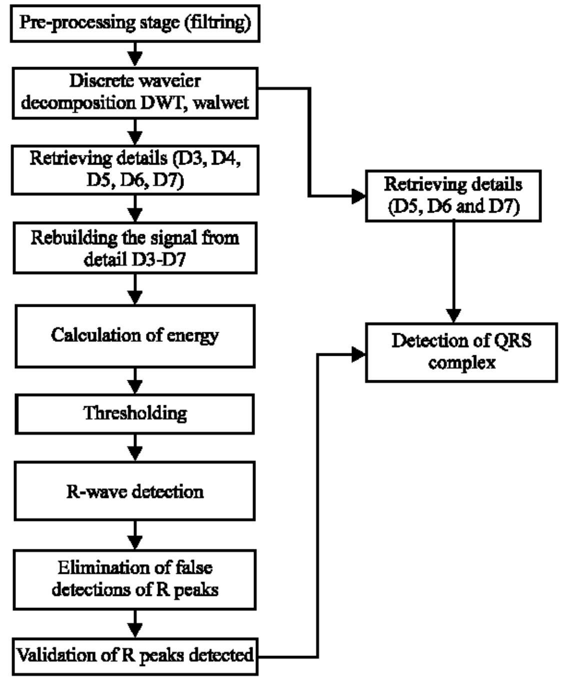


Fig. 2: Block diagram of the principle adopted in the QRS complex detection algorithm

The ECG signal from the pre-processing stage where it is subjected to a filtering operation of the different noises which contaminates it is decomposed into a wavelet. The choice of the mother wavelet used is of paramount importance in wavelet applications.

In reality there is no well-defined criterion for the selection of the mother wavelet and this choice depends very much on the nature of the application and differs from one application to another.

Several studies (Zidelmal *et al*., 2012) on the wavelet ECG signal analysis found that the ‘Daubechies’ wavelet family and more particularly the ‘db4’ wavelet is best suited for processing of the ECG signal because its shape is similar to the QRS complex.

Thus in the rest of this research, the Daubechie’s db4 mother wavelet is chosen to be used for the decomposition of the ECG signal. The choice of the level of decomposition is also a parameter to be taken into account. In this algorithm, we decomposed the eight-level ECG signal by referring to previous work carried out at the Biomedical Engineering (GBM) laboratory (Ellis *et al*., 2011) which shows that this choice is judicious, since, it makes it possible to clearly distinguish the QRS complex P and T waves and baseline.

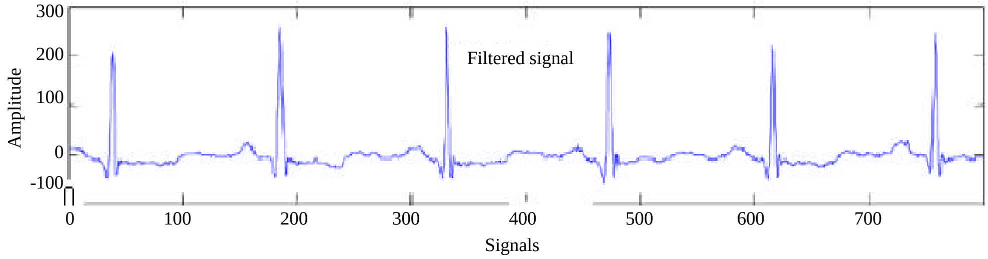


Fig. 3: Patient '100' filtered ECG signal

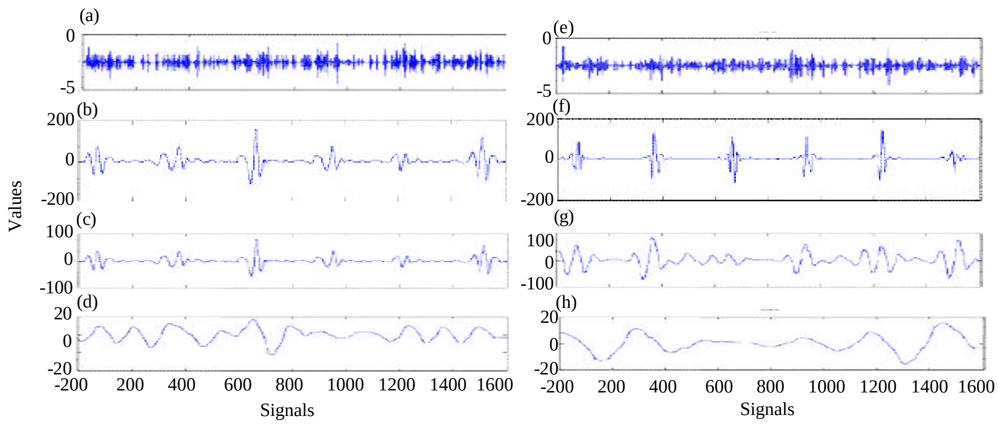


Fig. 4: The eight details of the ECG signal decomposition of the patient '100'; a) CD 1; b) CD 2; c) CD 3; d) CD 4; e) CD5; f) CD 6 and g) 7

The principle adopted in the algorithm begins by detecting the R-peaks of the QRS complex with its amplitude which predominates the ECG signal and then the Q and S waves are detected.

Figure 3 shows a portion of the ECG signal of the patient '100' in its filtered version from the pre-processing stage whereas the eight details of the wavelet decomposition 'db4' of this signal are shown in Fig. 4.

**The detection of the R peak:** Peak detection R is the most important step in the detection of the QRS complex since the detection of the other waves depends on the reliability of this first step. In order to detect these R peaks, the detailsspecific to the QRS complexes will be selected.

Eight wavelet decomposition levels are performed on the pre-processed ECG signal using the 'db4' wavelet as shown in Fig. 4. Details D3-D6 are retained and all other details are deleted.

The reconstruction of the signal is thus carried out from the details D3-D6 this makes it possible to keep the QRS complexes in the obtained signal and to eliminate the other components at low and high frequency. The resulting signal is shown in Fig. 5b.

The signal obtained is raised to the square in its positive part. This operation makes it possible to accentuate the R wave and to attenuate the other waves as illustrated in Fig. 5c. Adaptive tyhresholding is performed on this signal to detect peak R.

Based on the impossibility of having two heartbeats in <0.25 sec, a final step of eliminating the falsely detected R peaks is carried out before validating the detection results. The final result of detection of the R waves is illustrated in Fig. 6.

**Detection of Q and S waves:** Once the R peaks are detected, the Q and S points must be identified to detect the QRS complex completely. In general, waves Q and S have a high frequency they are of small amplitude and their energies are mainly on small scale. To do this the decomposition coefficients of D5-D7 are retained to reconstruct the signal as shown in Fig. 7a. All other details of the signal have been removed.

Moreover, the waves Q and S are negative deflections which occur either side of the peak R over a maximum interval of 0.1 sec in a usual manner. The left hand wave noted Q is taken to be the minimum amplitude that precedes the R peak and the S wave the minimum amplitude that follows it. The Q and S wave detection result is shown in Fig. 7b, c, respectively.

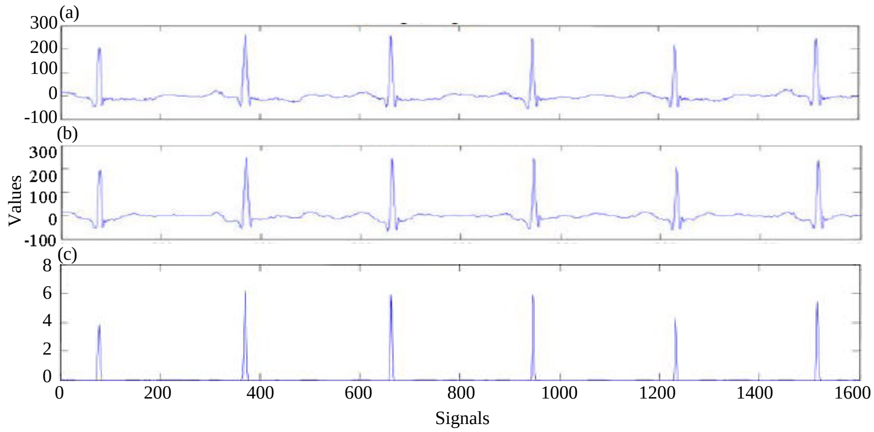


Fig. 5: a) Orignal signals ECG signal; b) Signal reconstruction from details D3-D6 and c) Signal energy

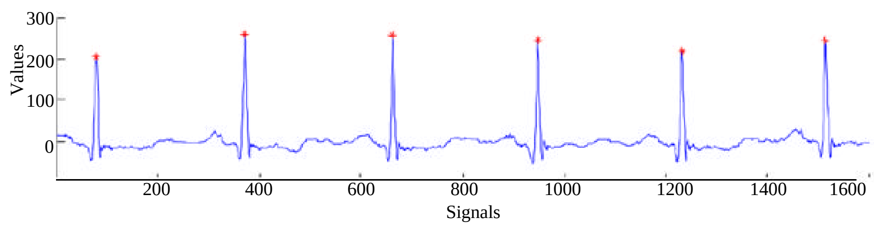


Fig. 6: Detection of R waves

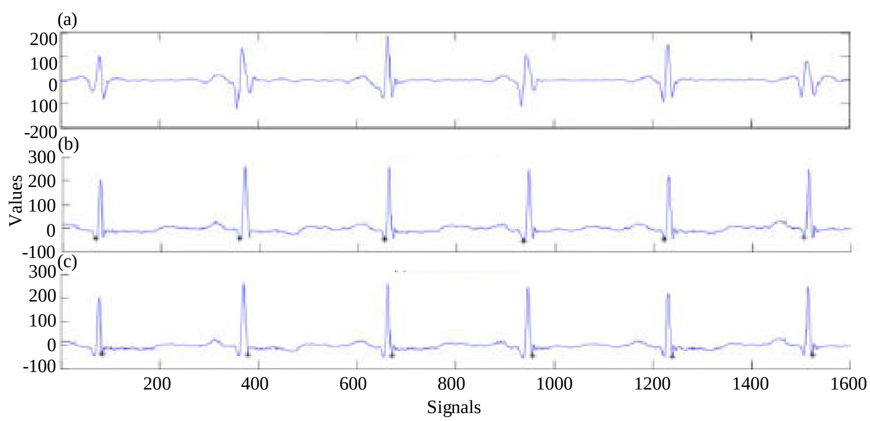


Fig. 7: a) Reconstruction of the signal from details D5-D7; b) Detection of the Q wave and c) The S wave

**Segmentation of heartbeat:** This study present the theory of wavelet networks for automatic classification of heartbeat. The neural networks (Gao *et al*., 2005) the double density wavelet functions (Sanyal *et al*., 2012) can be combined in a same system called a wavelet network. A link between the two techniques has been established in different ways and byseveral researcher.

A wavelet network generally consists of a feed forward neural network with a hidden layer whose activation functions are derived from a family of double density wavelets.

The wavelet network was originally designed to solve problems of function estimation. Given a series of observed values of a nonlinear function, a wavelet network can be formed to learn the modeling of this function and thus, to calculate an expected value for a given input.

The wavelet network was introduced by Zhang and Benveniste (1992) as an alternative to feed-forward neural networks for the arbitrary approximation of nonlinear functions. Zhang and Benveniste have described a wavelet lattice structure allowing parametric modeling of multidimensional functions g(x) according to the expression:

$$\hat{g}_i(x)=\sum_{i=1}^{L} w_i.\psi(D_i.R_i.(x-T_i))+\bar{g} \tag{10}$$

Where:

L = The number of neurons on the input layer

$D_l$, $R_l$ and $T_l$ = The affine transformations applied to the vector x before processing by the mother wavelet in the neuron of index 1

G = The continuous component (mean value) of the approximation

The vector p groups all the parameters of the wavelet network, namely the weights the coefficients of the affine transformations and G. The parameter p is adjusted by an iterative optimization algorithm which aims to minimize the residual:

$$\rho(p)=\sum_{\chi}\left[g(x)-\hat{g}_p(x)\right]^2 \tag{11}$$

For all available values of input x.

**Wavelet network model:** When dealing with modeling or classification problems it is often common to deal with multi-variable inputs and for this it is necessary to use multidimensional wavelets whose expression is given by:

$$\psi_j(x)=\prod_{k=1}^{N}\psi(Z_{jk}) \tag{12}$$

Where:

$$Z_{jk}=\frac{xk\pm b_{jk}}{a_{jk}} \tag{13}$$

Where:

$x_k$ = kth component of the input vector

x and $z_{jk}$ = Component centered by $b_{jk}$ and expanded by a factor $a_{jk}$

A multidimensional wavelet is defined as the product of one dimensional wavelets, it is also said that thewavelets are separable. The hidden neurons of a wavelet array can be considered as multidimensional wavelets.

The wavelet network can be considered to be made up of three layers. A first layer with N inputs representing the number of samples of the input vector a hidden layer constituted by L neurons with multidimensional wavelet functions used as activation functions and an output neuron (or linear neuron) which will have the role of receiving all of the different weighted outputs of the multidimensional wavelets of the preceding layer. The neurons in a layer are connected to all neurons in the next layer and only to those neurons. The values are propagated in the feed-forward direction, i.e., from the input layer to the output layer.

Following are the merits of wavelet networks compare to neural network. Wavelets are functions that decrease rapidly and tend to zero in all directions of space. They are therefore local if the expansion coefficient $a_j$ is very small.

The shape of each one-dimensional wavelet is determined by two adjustable parameters (translation and expansion) which are structural parameters of the wavelet. Each one-dimensional wavelet has two structural parameters, so, for each multidimensional wavelet the number of adjustable parameters is twice the number of variables.

**Learning wavelet networks:** Learning of wavelet networks is supervised using well-annotated examples (a learning base). Let a learning base consisting of D examples each example n consisting of a vector xn (k) applied to the inputs of the wavelet network and of the vector 'dn (k)' corresponding values for the outputs. The value of 'yn (k)' corresponds to the actual output of the network which corresponds to the input '$x_n$ (k)'.

The learning of a wavelet network is defined as an optimization problem which consists in identifying the network parameters minimizing a global error function (cost function). The network parameters can be divided into two classes:

- The structural parameters of the wavelet functions that is to say the translations and the dilations
- The synaptic weights of the network

The definition of this cost function is essential since it is used to measure the difference between the desired outputs of the model and the network outputs observed. The function most commonly used is the, so-called quadratic error function, the definition of which is as follows.

For each example $x_n$ (k) (n∊D) of the learning base, a quadratic error function defined by the following equation is computed. In a general case, it is also assumed that the wavelet network has a number of output neurons:

$$e(n)=\frac{1}{2}\sum_{r=1}^{R}\left[d_r(n)-y_r(n)\right]^2 \tag{14}$$

Where:

R = 1, ..., R= Number of output neurons

n = 1, ..., D= Number of learning examples

k = 1, ..., N= Number of input neurons (length of the input vector)

j = 1, ..., L = Number of hidden neurons

For the whole training set we can define the cost function (also called the Mean Squared Error (MSE)):

$$E(n)=\frac{1}{D}\sum_{n=1}^{D}e(n) \tag{15}$$

The principle of the learning algorithm is to calculate the contribution of the network settings to minimizing the error using the back propagation algorithm of the error. The optimization technique used requires the computation of the gradient vector of the cost function with respect to the vector of adjustable parameters. Its expression is given by the following equation:

$$\frac{\partial E}{\partial \theta}=-\sum_{n=1}^{D} e(n)\frac{\partial y(n)}{\partial \theta} \quad (16)$$

θ is the vector grouping the set of adjustable parameters:

$$\theta: \{a_{jk}, b_{jk}, w_j, w_{jk}\}, j = 1, ..., L, k = 1, ..., N \quad (17)$$

where, ∂ y(n)/∂ is the value of the gradient of the actual output of the network with respect to the parameters ∈.

The determination of the number of neurons in the hidden layer is one of the most critical tasks in the design of neural classifiers.

Unlike the number of neurons in the input layer that is set according to the input vector (three inputs) and the number of neurons in the output layer that is represented by a single neuron to indicate the output class, the number of hidden neurons is chosen empirically after several tests. The number of hidden neurons considered is that the learning error and test are minimal.

## RESULTS AND DISCUSSION

**Description of the MIT-BIH data base:** The MIT-BIH database (Nazmy *et al*., 2010) is a universal database containing 48 half hour two-way records (DII and V5). It has been collected by researchers to be used as a reference for the validation and comparison of algorithms on the ECG signal. Each ECG recording is sampled at a frequency of 360 Hz.

The main advantage of this database is that it contains a large number of cardiac pathologies which makes it possible to validate the algorithms on a large number of ECG signal cases. The records correspond to subjects that are 25 men aged 32-89 years and 22 women aged 23-89 years.

The signals are numbered from 100-124 for the first group that includes a variety of waveforms and from 200 to 234 for the second group that includes a variety of pathological cases.

Each record has been annotated independently by several cardiologists (two at least) which allows for more reliable studies.

Annotation file (* .atr) it comprises the positions or the moments of appearance of the peaks R of the QRS complex of the given signal. These locations were manually marked by several cardiologists. There is a number giving the order of the R peak as well as a mark corresponding to the QRS type (normal or abnormal).

**Collection of the database and choice of targeted arrhythmias:** An arrhythmia corresponds to any disturbance in the regular rhythmic activity of the heart (amplitude, duration and shape of the rhythm). From the point of view of the diagnosis of arrhythmia, the most important information is contained in the QRS complex.

There are different categories of heart beats which are Normal beats (N) Left Branch Blocks (LBBB) Right Branch Blocks (RBBB) premature ventricular contractions) and Premature Atrial Contractions (APC). As mentioned earlier, all beats used are extracted from the records in the MIT-BIH database.

**Feature input for classifier:** The choice of the input vector of a classifier is very important for the correct recognition of cardiac pathologies. Indeed, the quality of the classification depends very much on the relevance of the parameters of the input vector.

Our choice of characterization of different beats heart disease is established according to the targeted pathologies. The characterization parameters chosen are the same parameters on which the cardiologist bases his diagnosis.

**The RRp interval:** We call RRp the distance between the peak R of the present beat and the peak R of previous beat. This parameter is an indicator of prematurity of the beat.

**The interval RRs:** We call RRs the distance between the peak R of the present beat and the peak R of next beat.

**The ratio of RR intervals (RRs/RRp):** The RRs/RRp ratio is a parameter that characterizes the rhythm. In the case of a rhythm this ratio is close to 1 but it can largely exceed this value in the case of a premature beat.

**The width of the QRS complex:** This parameter is important for the identification of pathological pulses of origin ventricular arrhythmias these types of arrhythmias are generally characterized by a large complex QRS.

**The amplitude of the R wave ($R_{amp}$):** This parameter is also important for the identification of pathological of ventricular origin which are often characterized by either attenuation or amplification of the amplitude of the QRS complex.

The algorithm of detection of the QRS complexes that we have developed in the third section allows us to calculate the values of these different parameters for the characterization of the cardiac beats.

**Performance evaluation parameters:** The classified heartbeat will be compared with the annotations associated with each record in the MIT database to determine the error of the classification:

$$\text{Accuracy} = \frac{\text{True positive+True negative}}{\text{True positive+True negative+False positive+False negative}}$$

$$\text{Precision} = \frac{\text{True positive}}{\text{True positive+False positive}}$$

$$\text{Sensivity} = \frac{\text{True positive}}{\text{True positive+False negative}}$$

The results of the classification of the five types of heart beats (N, PVC, APC, RBBB and LBBB) by the wavelet network that we have implemented are illustrated in the form of a confusion matrix illustrated in Table 1.

From the results summarized in Table 1 we have to note that most unidentified normal beats are those classified by the wavelet network as beats of the APC type (5 beats in total).

Similarly, the number of beats (LBBB) misclassified (RBBB) and the number of beats (RBBB) classified as beats (LBBB) are 2 and 3, respectively. This gives more credibility to the five representative parameters that we used in the characterization of heartbeats.

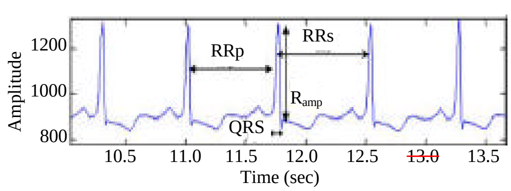


Fig. 8: Characterizationparameters on a heartbeat of a healthy subject [RRp RRs RRs/RRp QRSR$_{amp}$]

Table 1: Confusion matrix

| Confusion | N | PVC | RBBB | LBBB | APC |
|---|---|---|---|---|---|
| N | 48 | 3 | 0 | 2 | 5 |
| PVC | 0 | 44 | 1 | 2 | 10 |
| RBBB | 6 | 2 | 50 | 3 | 1 |
| LBBB | 3 | 1 | 2 | 48 | 1 |
| APC | 3 | 2 | 1 | 3 | 52 |

These parameters make it possible to improve the discriminating capacity of the wavelet network and more particularly in the discrimination of the morphologically similar beats (the normal beats (N) with beats of the APC type or the beats of the RBBB type with beats of the type LBBB).

Concerning beats ofthe PVC type it should be noted that thereis no beat classified as a normal beat, a single beat classified as a beat of the RBBB type and 2 beats classified as beats of the LBBB type. This comes down to the morphological difference between PVC type beats with other types of heart beats.

For the evaluation of the performance and quality of the wavelet network classification we calculated the classification rate, specificity and sensitivity (PVC, RBBB, LBBB and APC). These results are summarized in Table 2. The results presented in Table 2 show satisfactory classification rates of the proposed method. Discrimination between heart beats is very acceptable for different classes.

**Comparison with other methods:** For the evaluation of the results obtained from the classification of the heart beats by the wavelet network a comparative study carried out with other works using classifiers based on neural networks and which are cited in literature such as the self-organizing cerebellar model articulation controller. The below table summarizes the results obtained for the classification of cardiac arrhythmias by the proposed method and other methods.

Therefore, all these factors will influence the results of the classification of the heart beat. It is evident from Table 3 that the results of the implemented wavelet network are relatively satisfactory with respect to the results of the others research of the classification rate of the ECG beats.

This can be explained by the use of wavelet functions as activation functions in hidden neurons which allows the wavelet network to have more adaptive parameters (the parameters of the wavelet functions that are the parameters of translation and expansion parameters) for the prediction of its final output.

Table 2: Results of wavelet network classificationfor different types of heartbeats

| Evaluation parameters/Type of beats | Values (%) |
|---|---|
| **Specificity (%)** | |
| N | 99.23 |
| PVC | 99.05 |
| **Sensitivity (%)** | |
| RBBB | 98.43 |
| LBBB | 98.51 |
| APC | 98.51 |
| **Classification rate** | |
| Total | 99.42 |

Table 3: Comparison of results

| References | Methods | Description | Classification rate (%) |
|---|---|---|---|
| | Proposed | Wavelet transform with wavelet neural network | 99.78 |
| Wang *et al*. (2013) | FCM+PCA+WT +NN | Fuzzy C-means, principal component analysis and wavelet transform with neural network | 99.17 |
| Nazmy *et al*. (2010) | NF | Neuro fuzzy classifier | 99.42 |

Thus, these results show that the method studied (the wavelet networks) in this research has the potential to solve problems of automatic recognition of heartbeats and consequentlyit can be considered as efficient method for ECG classification.

## CONCLUSION

Through this study, we explored the capabilities of artificial neural networks and wavelet functions in the same hybrid system combining the two techniques to solve a classification problem of cardiac arrhythmias. The proper characterization of the ECG signal by relevant parameters is a necessity for discrimination between different targeted arrhythmias. We note that the wavelet functions can be considered as parameterized functions at the level of the neural networks whose parameters of translation and expansion are adjustable during thelearning.

Since, the wavelets are local functions, the problem of the initialization of the dilations and translations is very important. We have used a simple initialization procedure that takes this property in to consideration.

Indeed the results showed that the proposed method can be considered as a promising prototype for ECG classification with a good accuracy of more than (99.42%) even though the representative vector of the beats consists only of five parameters which shows the effectiveness and relevance of the parameters chosen.

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