Wavelet based on Electrocardiogram Signal Analyses for Classification and Diagnosis By Neural Networks

A. Kachouri, M. Ben Messaoud and A. Dallali
LETI, Laboratoire Electroniques et Technologie de l’Information.
Ecole Nationale d’Ingénieurs de Sfax, BP W 3038 Sfax-Tunisie.
Tel : (+216) 74 274 088 Fax: (+216) 74 275 595.
Email : Abdennaceur.kachouri@enis.rnu.tn

Abstract:
The ECG signals are the most obvious observable of the human heart and as such have been subject to intensive analysis with regard to their significance in the context of pathologies. The authors studied a novel method for analyzing electrocardiogram signal by using wavelet technique. The analysis was pursued by a clinical classification by using neural networks techniques. We present an ECG signals analysis by wavelet transforms. Digital Wavelet Transform algorithm is applied to decompose the non-stationary and quasiperiodic ECG signal. The Daubechies wavelet ‘db3’ of 3rd level is used for the best possible compression to decomposed ECG signals. Through the different morphology ECG waveform, we extract the decompositon parameter for cardiology diagnostic applications. The extraction of ECG parameters is used in learning phase of neural networks. The network assures the classification of ECG for several pathologies and morphologies with the main focus for sure. The experimental analysis and the verification of classification are presented. In the first part of the paper, we present the characteristics of different part of ECG: by insisting on their electric properties (P, QRS and T waves). Second part gives the Wavelet transformation coefficients of different signals. Next, the neural network classification methodology is exposed. The learning phase of the network is based on the wavelet decomposition coefficients. Finally, the result of the ECG classification is presented with the aim of an automatic diagnosis of the patients' diseases.

Key words
ECG, Wavelet transforms, neural network, classification and diagnosis.

INTRODUCTION
The ECG will remain indispensable system for examination and diagnosis of the most treatment of affections heart patients. Therefore, It is a main tool for the diagnosis of rhythm; infarcts and the other patients heart pathologies. It is known that electrocardiogram (ECG) signals are used extensively in different monitoring and diagnostic cardiology applications [kao 96]. So, a Holter monitor produces a large amount of nonstationary and quasiperiodic data, which are difficult to directly classify the ECG frames. Many methods have been proposed to solve the problem. They are divided into two categories: direct and transformation methods [Sch 98].

Over recent years, Wavelet Transforms play an increasing role in the medical signal analysis. So, They are applied to a wide variety of biomedical signals including: the ECG, EEG, EMG, Echocardiograms, blood pressure trends and DNA sequences [Zha 97]. The aim of this contribution is to decompose and compress the original signals (Normal and abnormal frames of successive ECG) by Wavelet technique, and then to classify them by the neural network as shown in figure 1.

---

The efficient compression techniques are needed to process ECG signals. Several statistical characteristics of ECG frames are extracted to depict and compress them in our scheme. The approximation and details are deduced to express the shape and the zooming of ECG waveforms. It is necessary to compress ECG signals by employing the morphological characteristic of ECUs. A high compression ratio and a low reconstruction error are needed. With the use of the Neuronal Network technique, we can after classify the compression...
ECG signals by employing the morphological characteristic of ECGs.

Characteristics of the ECG

The ECG represents the propagation of electrical waves through the respective regions of the heart (SA Node, Arial Muscle, AV Node, Atrioventricular Bundle, Left and Right Bundle Branches). These signals are the most obvious observable of the human heart and have been used to intensive analysis since of their significance in the context of pathologies. It is measured as the surface potential associated with these waves. Usually, the listing of the electrical waves variations on the papers constitutes the ECG. The waves ("P wave", "QRS wave", "T wave" and sometimes "U wave") will be used to identify the different sections of the ECG cycle. The figure 2 shows the temporal characteristics of normal ECG.

![Figure2: temporal characteristics of normal ECG.](image)

The analysis of the P, QRS, T is essential in diagnosis and in the treatment of the confusions of heart rhythm. This help as to establish the origin of pains thoracic, understands the measure of amplitudes and durations of various registered. The table 1 summarizes the electric properties of a normal ECG (waves P, QRS, T). Therefore, it is necessary to assess to the time period in which the analyzed ECG signals can be considered stationary.

<table>
<thead>
<tr>
<th>Wave type</th>
<th>Magnitude (mm)</th>
<th>Duration(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>P wave</td>
<td>3</td>
<td>0.08 to 0.12</td>
</tr>
<tr>
<td>QRS complex</td>
<td>5 to 20</td>
<td>0.06 to 010</td>
</tr>
<tr>
<td>T wave</td>
<td>5.5</td>
<td>0.15</td>
</tr>
</tbody>
</table>

Table 1: The characteristic of the normal ECG

In biological systems, this is especially difficult to evaluate, since a number of subsystems interact. For the ECG data studied, it was attempted to provide constant environmental conditions in order to minimize any effect that would compromise the stationarity of the heart cycle. An example for this situation is the influence of the respiratory cycle on the heart, having a very different pseudo-period than the heart rate. Thus, the problem of stationarity is related on the condition of the time period where it is considered constant. As these signals are not stationary, it is necessary to use more sophisticated techniques of treatment of signals. The wavelet-based ECG data compression method presented here and its compatibility with the current application to extracted ECG wavelet composed from compression approaches can be summarized as follows, for more details refer to [Hil 95]–[Gon 99].

Compression Algorithm

In this section we summarize an effective method to compress and characterize ECG signal using Discrete Wavelet Transform (DWT) [Ben 01].

The method

The literature agrees on the fact that Percent Root square mean Difference PRD is not sufficient to access the quality of the compression or the modeling of ECG signal [Sch 98]. Instead, visual inspection by medical experts are usually proposed to verify performance.

In our application, ECG data from initial training set were decomposed into eight wavelet scales. The compression algorithm begins at level j=3 when compression ratio CR is less than 13%, Where

$$CR = \frac{\text{comprssed data}}{\text{original signal samples}}.$$

One compares initial ECG signal \(x(n)\) and reconstruction signal \(x_a(n)\) from scaling coefficients \(a_i\) by ignoring the coefficients \(d_i\) (i=0…j). The algorithm prompts when approximation error is less then a given value \(\lambda_i\) and the compressed signal is \(x^*(n)=x_a(n)\).

Notation

- \(x_a(n)\) the reconstruction signal from approximation coefficients \(a_i\).
- \(x_d(n)\) the reconstruction signal from details coefficients \(d_i\).

If the algorithm does not converge, then the details threshold coefficients \(d_i\) (i=0…j) are considered and compression signal \(x^*(n)=x_a(n)+\sum d_i\) is obtained for given level \(j\) when a fixed mean squared error \(\lambda_3\) is hold.

This algorithm is illustrated in figure 3.
SIMULATION RESULTS

To decompose the ECG signal, the simulation algorithm is performed under Matlab software using Wavelet Toolbox. We set the threshold $\lambda_1 = 0.7684\%$, this value is fixed for all the earlier analysis with the Daubchies wavelets (dbN) and Coiffet ones (coifN). One of the goals of the present work, is to reach a high compression ratio so for expressing the amount of data, i.e. the essential information, which is necessary for recovering the input signal with CR<13%.

Selection of wavelets

In this section, we applied the proposed algorithm described earlier in order to select the wavelet which gives a good compromise between both PRD and compression ratio CR.

$$PRD = 100 \cdot \frac{\sum_{n=1}^{N} (x(n) - \hat{x}(n))^2}{\sum_{n=1}^{N} (x(n))^2}$$

We begin by analyzing of a normal heartbeat ECG in order to select the appropriate wavelet that fulfilled our analysis in the ECG contain disease. For this purpose we have chosen the Daubechies dbN (N=1...12) and Coiffet coifN (N=1...5) wavelets. These wavelets have been chosen in the present work because they provide a much more effective analysis than obtained with other wavelets.

To examine the effect of the wavelet on the performance criterion (low PRD and high CR), Table 2 summarizes the simulation result of appropriate wavelet.

<table>
<thead>
<tr>
<th>Level</th>
<th>Decomposition parameters</th>
<th>Coefficient number</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Min</td>
<td>Max</td>
</tr>
<tr>
<td>5</td>
<td>-0.8955</td>
<td>0.5451</td>
</tr>
<tr>
<td>6</td>
<td>-0.5685</td>
<td>0.7161</td>
</tr>
<tr>
<td>7</td>
<td>-0.1455</td>
<td>0.1067</td>
</tr>
<tr>
<td>8</td>
<td>-0.3144</td>
<td>0.5482</td>
</tr>
</tbody>
</table>

Table3: parameters of learning of a normal ECG

As well as the previously, we extracted characteristic parameters of the ECG signals for various pathologies. These decomposition parameters constitute a database for the learning NNs.

The approach presented here will provide a new hybrid and interactive framework focusing on understanding the wavelet compression theory with Neuronal Network classification. Typically, for a given wavelet transform, there exist some fixed zones of spectral vectors that are to be kept within the compression process.

NEURAL NETWORK FOR CLASSIFICATION

The Neural Networks are applied for the classification, and identification the ECG pathology. In the current approach, these can easily be updated and reprogrammed based on certain parametric variations within typical ECG pathology by simply increasing or decreasing the sizes of the fixed selected zones of the spectral vector and analysis clinical ECG data. The parameters are extracted from wavelet transform and alterations time-scale of different type of ECG signals.

With the aim to have a correct and fast learning, we separate the neurones network into four blocks corresponding to the number of decomposition levels, which contain the maximum of information concerning the signal under study. The learning coefficient of neurones network is chosen equal to 0.769. The global architecture is presented in the figure 6.
Variation of PRD in function of CR with the chose of wavelets dbN

![Graph](image)

**Fig. 4** Variation of PRD in function of CR and the dbN wavelet order.

Variation of PRD in function of CR with the coifN wavelet order

![Graph](image)

**Fig. 5** Variation of PRD in function of CR and the coifN wavelet order.

<table>
<thead>
<tr>
<th>ECG</th>
<th>Normal</th>
<th>Necrosis</th>
<th>Ischemia</th>
<th>TF</th>
<th>TV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Classes</td>
<td>1</td>
<td>3</td>
<td>5</td>
<td>7</td>
<td>9</td>
</tr>
<tr>
<td>Output</td>
<td>0.1</td>
<td>0.3</td>
<td>0.5</td>
<td>0.7</td>
<td>0.9</td>
</tr>
</tbody>
</table>

**Table 4: classification of ECG signals**

![Diagram](image)

**Fig. 6** The global architecture of the neural network.

As apparent in figure 7, three layers forms each block of neural network (NN). The number of neurones in the input layer is equal to the elements of the input vectors (5, 6, 8, or 12 elements). The number of neurones in the hidden layer is optimised according to the learning error. The single output neurone, allowing to easily classification according the abnormalities ECG signal, is used. The output values of (NN) are normalized between 0 and 1. So, 0.1 value corresponding to the normal ECG, 0.3 for the case of Necrosis, 0.5 for the Ischemia case, 0.7 for the TF and finally and 0.9 for the case of Ventricular fibrillation (VF).

To avoid any overlapping classification, we have chose 0.2 as the step variation between classes. The table 4 gives the associated decimal number for every class.

The retro-propagation method is applied during the learning phase. Thus, the adaptation of weights between layers is given by the gradient method. In the global architecture of the neural network, the output vector (G1… G5) indicates the class of the ECG according to the inputs vectors (v1, v2, v3, v4) deduced from the wavelet decomposition of ECG.

If the elements of the vector G are identical, automatic diagnosis is concluded. It indicates that the parameters that characterise the various decomposition levels correspond to the same ECG. If the elements of the vector G are different then the identification failed due to powered database. For example, if all Gi are equal to 0.1 for i = {1, 2, 3, 4}, it implies that this ECG corresponds to the case of a normal ECG.
SIMULATION RESULTS

The following results are concentrated on the analysis and modeling aspects. The implementations of the algorithm in MATLAB software are not presented.

During the learning phase, we applied the inputs vectors in a sequential way to the NNs for various classes of ECG. To grow the database, we add a white noise to the original signal of various pathologies. Every class of ECG contains some similar variants: 9 vectors of class 0.1, 9 vectors of class 0.3, 11 vectors of class 0.5, 12 vectors of class 0.7 and 12 vectors of class 0.9.

The results of training phase are illustrated in the figure 8.

To verify the result of the network learning with reducing interval error, a set of examples of ECG are injected to the neural network.

The figure 10 illustrates the result of verification phase of the different ECG.

In bottom, the error curve illustrates the smallest values obtained (less than 3 %).

Some attempt of learning of the NNS, for various abnormalities of the ECG, by adjusting weights and ways of the NNS, allows us to find results these curves of evolution of which are presented in the figure 5.

CONCLUSION

In this study, a new method for analysing electrocardiogram signal using wavelet technique is presented. Knowledge extraction from a trained three-layer perceptron is considered. The main results obtained from the application of the Wavelet Transformation for the analysis of signals ECG allows the origin of the characteristic parameters of the ECG, as well as the filtering of these signals. These parameters extracted by Wavelet Transformation of the ECG, are considered by the learning of a neural network. This neural network is used for the classification of studied signals ECG. This is a considerable tool for the doctor and the cardiologist for a cardiovascular consultation of different kind of pathologies.

BIBLIOGRAPHY


[Sub] ATLAS D’ELECTRO-CARDIOGRAPHIE Peritrate; la Direction Médicale des Laboratoires Substantia.


Internet ressources

http://www ondelette.com, 98, 99,2000, Daniel Lemire
http://c.valens@mindless.com, 1999; A Really Friendly Guide to Wavelets.
Figure 8: (a) simulation result of learning phase

Figure 8: (b) zooming of level 0.3

Figure 9: Weight and bias evolutions.

Figure 10 result of verification phase.