Automatic Detection of Arrhythmias Using Wavelets and Self-Organized Artificial Neural Networks

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Abstract— The arrhythmias or abnormal rhythms of the heart are common cardiac riots and may cause serious risks to the life of people, being one of the main causes on deaths. These deaths could be avoided if a previous monitoring of these arrhythmias were carried out, using the Electrocardiogram (ECG) exam. The continuous monitoring and the automatic detection of arrhythmias of the heart may help specialists to perform a faster diagnostic. The main contribution of this work is to show that self-organized artificial neural networks (ANNs), as the ART2, can be applied in arrhythmias automatic detection, working with Wavelet transforms for feature extraction. The self-organized ANN allows, at any time, the inclusion of other groups of arrhythmias, without the need of a new complete training phase. The paper presents the results of practical experimentations.

Keywords-arrhythmia detection; Wavelets; self-organized artificial neural networks; ECG

I. INTRODUCTION

The cardiac diseases are one of the main causes of death in developed and under developed countries [1]. These deaths could be minimized with early detection of cardiac arrhythmias made by the electrocardiogram (ECG). The ECG is the record of the electrical potentials, generated by the human heart that hits the body surface [2]. The arrhythmias and abnormal cardiac rhythms are very common disturbs and may cause serious risks to life. These disturbs are characterized by the alteration of frequency or the rhythm of cardiac beats, being caused because of many reasons [3].

The automatic detection of arrhythmias using the ECG can be done through several ways (here are some examples [4], [5], [6], [7], [8], [9], [10], [11], [12], [13]). One of the most popular approaches is based on machine learning. Usually, machine learning approaches for automatic detection of arrhythmias are divided in three steps: pre-processing, feature extraction and processing the ECG signal. In the step of pre-processing, the signal generated by the electrocardiograph is segmented. In the step of feature extraction, the ECG signal is segmented and a vector of features is built. This vector contains a collection of data that better represents the signal. In the stage of processing, the

feature vector is used to training a classifier in order to be able to find eventually arrhythmias in an ECG signal.

In this work we used a self-organized artificial neural network (ANN) to detect (processing) arrhythmias. This kind of ANN allows the addition of new arrhythmias without having to redo the whole process. Thus, the main advantage of this approach occurs when it is necessary to adapt the system for detecting new arrhythmias. This is known as an incremental learning method [14], [15].

In the work described here, the pre-processing and feature extraction steps are made using the Wavelet transforms. The ECG samples (in time domain) are converted to time-frequency domain, generating Wavelet coefficients. The ANN (we used an ART2) is trained to group these coefficients based on their similarities. Finally, the clusters formed are classified by an algorithm developed in Java during a post-processing step.

The paper is organized as follows: the section 2 describes the ECG, the cardiac arrhythmias and the process of automatic detection of arrhythmias. The section 3 presents our approach for arrhythmias detection. In section 4 we present some experimental results. Finally, we present some conclusions and indicate some perspectives for future work.

II. THE ELETROCARDIOGRAM AND THE AUTOMATIC DETECTION OF ARRHYTHMIAS

In this section, is presented the foundations of the ECG, the cardiac arrhythmias and the process of automatic detection of arrhythmias.

A. The Electrocardiogram (ECG)

As the cardiac pulse travels by the human heart, electrical currents are propagated by the body. A small fraction of these currents reaches the body surface [3]. Putting electrodes over the skin, in opposite points of the heart, can be measured the electrical potential generated. This corresponds to the ECG. A normal ECG for one single cardiac beat is shown in the Fig. 1.
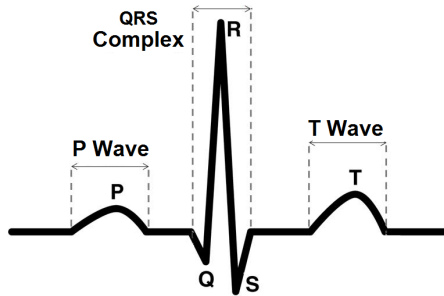
Figure 1.   Elements of normal electrocardiogram[1].

The normal ECG is composed by a P wave, a QRS complex and a T wave [3]. The QRS complex may not necessarily be composed by three waves (Q, R and S).

B.   *Cardiac Arrhythmias*

Arrhythmias can cause the death, so they are treated as a medical emergency. In function of their great incidence, the present work focuses on a specific group of arrhythmias called Premature Contractions[2]. The Fig. 2 presents an isolated Atrial Premature Contraction (APC), marked by the letter "A". The main characteristic of this arrhythmia is that the P wave is shorter than the normal one.
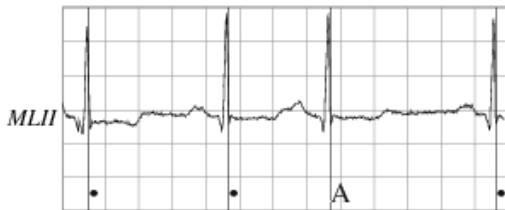

Figure 2.   APC arrhythmia (extracted from the record 100, [17]). Break the grid: 0.2 sec, 0.5mV.

The APC arrhythmia is very common in healthy people. It is caused by many factors like: smoking, sleepless, excessive coffee, alcoholism, and others [2].

There is also the Premature Ventricular Contraction (PVC). This arrhythmia can be seen on Fig. 3, represented by the letter "V".
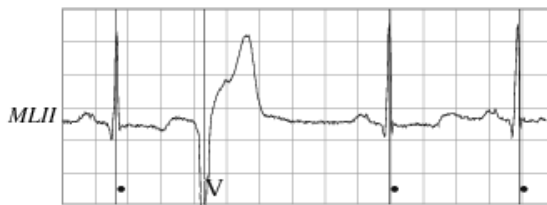

Figure 3.   PVC arrhythmia(extracted from the record 100, [17]). Break the grid: 0.2 sec, 0.5mV.

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[1]   The ECG presented in this figure is not real, is only an illustration to show the waves and the segments that form it.

[2]   This is a contraction that occurs before the time when they should be a normal contraction.

Some PVC arrhythmias are resulted by the same factors of the APC. Emotional irritability can cause PVC, too. Normally, this kind of arrhythmia is benign, however some PVC are the result of reentering signals originated from the limits of infarcted or ischemic cardiac areas. In these cases, the PVC can develop spontaneous ventricular fibrillation, which is lethal [2].

C.   *The main steps in automatic detection of arrhythmias using ANN*

The Fig. 4 shows the main steps commonly used to detect arrhythmias using ANN.
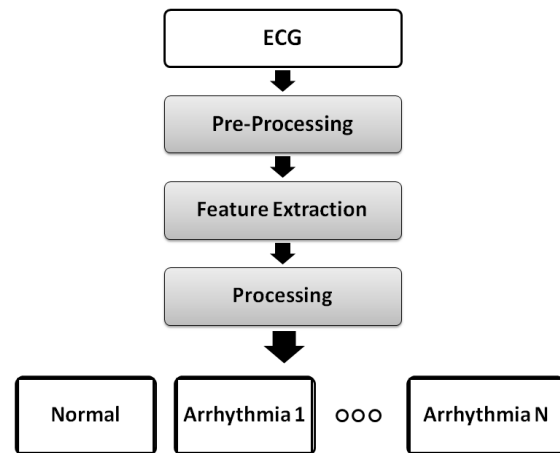

Figure 4.   Automatic detection of arrhythmias using ANN: overview.

The pre-processing is very important, because in this phase the ECG samples are selected.

Another important step is the feature extraction of the ECG. This step must be carefully studied, because it may affect the performance and accuracy of the entire process. The Wavelet transform has obtaining good results for feature extraction [16]. The application of a Wavelet transform over a signal shows additional information that was not previously known: when each frequency component occurs [18].

The last step is the processing, when the arrhythmias are identified. The ANNs are commonly used in this step, classifying or clustering the input signals [19]. In classification, an existent class will be assigned to the analyzed signal. In the clustering approach, the clusters are generated during the process based on the similarities between the input signals. So, a new signal can be added to an existent similar cluster or to a new cluster, if it is not similar to other signals.

III.   AUTOMATIC DETECTION OF ARRHYTHMIAS USING WAVELETS AND SELF-ORGANIZED ANN

This section presents our approach to classify arrhythmias using Wavelets and self-organized ANN. The Fig. 5 shows the overview of the approach. Each module is described in the next paragraphs.

We used the MIT-BIH Arrhythmia Database to test our system. This database [17] is the main reference for the development and evaluation of arrhythmias detectors.
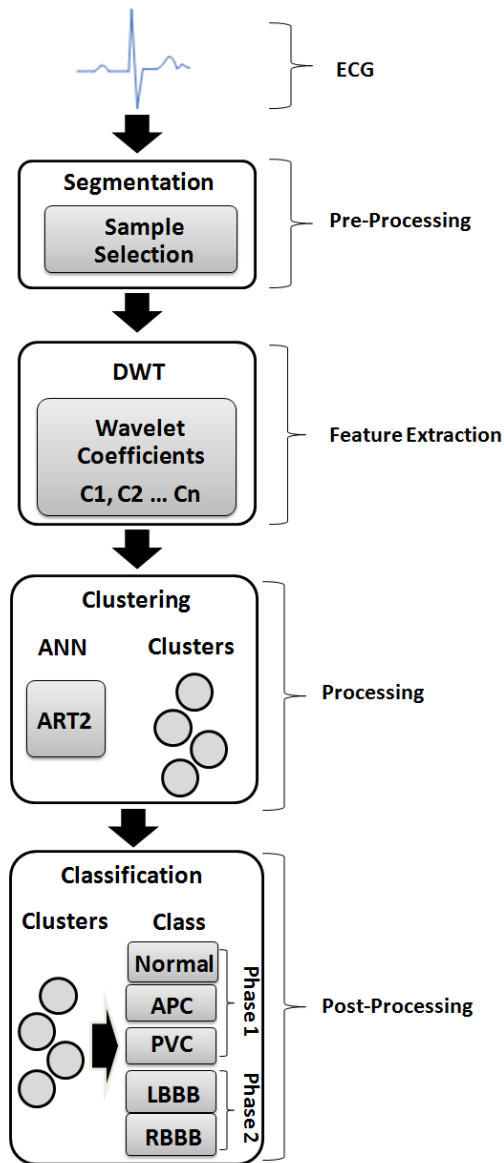

Figure 5.   The approach overview.

It was created by the Boston's Beth Israel Hospital over the years of 1975 and 1979 [22], being published in 1980. The database contains 48 records of ECG with arrhythmias, and each record contains 2 ECG leads. The hospital digitalized the waveforms with a samples rate of 360Hz and with 11 bits of resolution. Twenty-five of the 48 records were selected from a specific collection of exams and other 23 records were randomly selected to represent other arrhythmias [17]. Several specialists analyzed each cardiac beat included in the records, informing the occurrence or not

of an arrhythmia, in a total of 110,000 cardiac beat annotations [23].

The process starts by segmenting the entire database (Fig. 6). Normally, the first step in segmentation is the cardiac peaks detection. However, the MIT-BIH is already annotated. For each cardiac beat, one hundred samples were selected, being 50 samples before the peak and 50 samples after the peak. This interval contains the most relevant waves for the arrhythmia detection method.
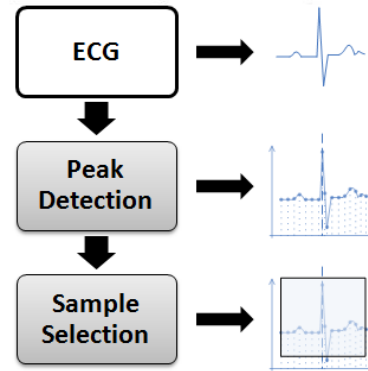

Figure 6.   The process of segmenting the ECG signal.

The samples selected (Fig. 7) are submitted to a Wavelet transform, consisting in the feature extraction process. We used a discrete Wavelet transform called Coiflet, with 4 levels of resolutions.
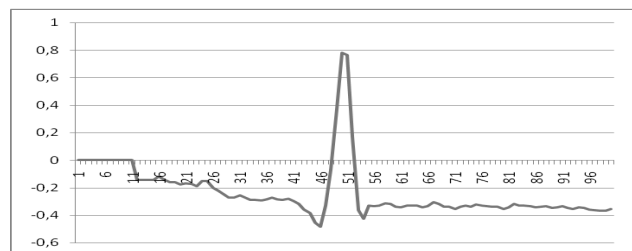

Figure 7.   Samples of the original ECG signal.

The Wavelet transform produces the Wavelet coefficients (one coefficient for each sample). They create the feature vector that will be processed by the ANN (shown in Fig. 8).

The Wavelet was parameterized in 4 levels, as recommended in [20] and [21], where some wavelets were compared.

The coefficients are submitted to the ANN. An Adaptive Resonance Theory (ART2) ANN [25], with 100 input units and 15 clusters, were used. The ART2 was chosen because it does not lose the knowledge acquired over time. Each feature (or wavelet coefficient) is submitted to the network, during the learning process (Processing step in Fig. 5).

TABLE III. COMPARISON BETWEEN THE ART2 RESULTS AND OTHER PUBLISHED WORKS.

Work	Arrhythmia		Number of arrhythmias analyzed	Accuracy	Standard Deviation
	APC	*PVC*			
ART2 ANN	**x**	**x**	**4**	**92.88%**	**0.03**
[8]		x	2	80%	12.91
[9]		x	1	96.90%	3.99
[10]		x	1	98.60%	5.69
[7]	x	x	4	98.30%	5.39
[11]		X	4	93.70%	0.79
[26]	x	X	2	90%	2.91

It is very relevant to remind that ART2 networks are plastic[3], so it is not necessary to retrain it when new groups of arrhythmias are added [25]. Actually, the training is performed only for the new groups, speeding the process.
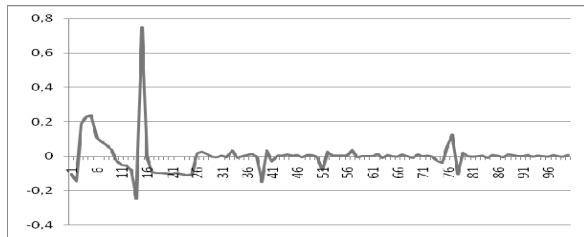

Figure 8.   Wavelet coefficients from feature extraction.

All parameters of ART2 are shown in table 1.
The parameters c and ρ were adjusted empirically.

TABLE I.   PARAMETERS VALUES USED IN THE ART2 NETWORK.

Parameter	Value	Description
t	100	Number of learning cycles
n	100	Input units
m	15	Output units
a	10	Lower level influence
b	10	Middle level influence
d	0.9	Activation of the winning unit output
c	0.1	Fixed weight used in reset test
ρ	0.99	It determines the rate of formation of clusters

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[3]   This is the property of ANN that allows the development of structural changes in response to experience, and adapt to changing conditions and repeated stimuli [24].

The ANN was trained with a collection of 1,800 cardiac beats (in a cross-validation process) and it was tested with a collection of 200 cardiac beats for each arrhythmia examined (phase 1: normal, APC and PVC; phase 2: normal, APC, PVC, LBBB and RBBB – details in section 4). The ANN was implemented in the SNNS and the tests were performed in a modified version of JavaNNS.

The clusters created in the training process were analyzed by an algorithm at the post-processing step.

In the first phase, this algorithm checked how many times the patterns (normal, APC and PVC) showed at each cluster. For the first phase it was used the normal beat and 2 arrhythmias (APC and PVC). In the second phase two new patterns (arrhythmias) were added: the LBBB and the RBBB.

After this initial analysis, the algorithm selected the output units (clusters) that have had the most number of examples for each pattern. At the end the classes are created.

IV.   EXPERIMENTAL RESULTS

The experimental tests were divided in two phases. In the first phase, we selected the normal, the APC and the PVC arrhythmias. In the second phase two new patterns (arrhythmias) were added: the LBBB and the RBBB.

The results for both phases are shown in Table 2. Table 3 confronts the results of our approach to some already published.

TABLE II.   RESULTS OBTAINED USING THE ART2.

Arrythimia	Accuracy	
	Phase 1	*Phase 2*
Normal Beat	92.9%	92.76%
APC	92.25%	92.08%
PVC	95.1%	95.22%
LBBB	-	90.9%
RBBB	-	93.43%
TOTAL	**93.42%**	**92.88%**

After the insertion of new arrhythmias the decrease in accuracy was expected but not significant (0.54%). The rate of success presented was calculated from the average of N classes (arrhythmias). Some aspects may be relevant to explain the results and to guide us for future research. The Coiflet proved to be very efficient representing the ECG and its arrhythmias. We consider the system achieved satisfactory results, which are similar to the ones already published. We should, however, pay attention that comparisons are not easy to establish since the approaches presented in Table 3 worked with different number of arrhythmias. It is important to emphasize that the proposed method is incremental and not lose the knowledge acquired when new arrhythmias are added.

During the tests, many different ART2 configurations were used. Initially, an ART2 with 100 input units and 3 clusters were trained. However, the results were not so good. It happened because the normal ECG has great similarities with the APC arrhythmia. After these initial tests, the number of cluster was empirically changed for 5, 10, 15, 20, 30 and 40. Several tests showed that the network with 15 clusters obtained the best result.

V. CONCLUSIONS AND FUTURE WORK

The main contribution of this work is to show that self-organized neural networks, as the ART2, can be applied in arrhythmias automatic detection, working with Wavelet transforms for feature extraction.

The obtained results are similar to the state of the art, indicating that better results can be found in future studies involving self-organized ANN and Wavelets. Other configurations of the ART2 network can be studied and tested to obtain better results.

Furthermore, it is relevant to highlight that new arrhythmias can be added to the proposed system. Indeed, the next steps of this work are to analyze the performance of other Wavelet families, like Daubechies, Haar and Symmlet. The use of the Daubechies, for example, proved to have similar efficiency comparing to Coiflet in [21].

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