CARDIAC ARRYTHMIA CLASSIFICATION BY NEURONAL NETWORKS (MLP)

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Abstract: Cardiac activity is one of the most important determinants of a patient's condition. It results in the appearance of several waves on the course of the electrocardiograph: it is the cardiac signal, the electrocardiogram: ECG. The analysis of the ECG signal and the identification of its parameters constitute an essential step for the diagnosis. However, a set of methods and algorithms are developed in view of the importance of this signal and its use in clinical routine in the diagnosis of cardiac pathological cases. This paper fits into this problem and proposes a classifier of cardiac arrhythmias by application of neural networks. The results were validated by ECG signals from the different patients in the MIT-BIH Arrhythmias database, and given a recognition rate of 94%, this rate of classification exceeds the results obtained in the literature.

Keywords: Neuronal Network , Classification, MIT-BIH data base, Electrocardiogram (ECG).

Introduction

Over the past decade, automatic preventive recognition of markers for cardiac arrhythmia in which numerous studies have been proposed. Which will, for the most part, exploit artificial intelligence and data mining approaches to automatically analyze ECG signals, which are difficult to perform manually. These systems improve signal quality (noise filtering), extract information that is not visible through direct visual analysis and provide a diagnosis that can provide sufficient support to doctors to make the right decisions. However, automating the detection of cardiovascular disease from the ECG signal is not trivial and gives the doctor a good diagnosis. In addition, the provision of a system with sufficient expertise to automate diagnosis is an extremely tedious task.

The presented work in this paper proposes classification of PVC beats, and is organized as follows:
In the first section, we introduced the problematic and then examined related works to classify cardiac arrhythmia in Section 2. The third section presents details works specialized in detection of the PVC pathology. The proposed approach is detailed in Section 4.
Our experimental results and a discussion are presented in Section 5. Finally, the conclusion is drawn and future work is suggested in the last section.

Related Works

In the literature, we find several techniques applying various methods, the goal of which is to simplify the reading of an ECG signal; we have been interested in the following works:
The ARTMAP (Adaptive Resonance Theory Mapping) theory was used in (Ham, 1996) to test two types of heartbeat (normal beat and beat of premature ventricular contraction). It gave a classification rate of 97%. In (Al-Nashash, 2000) ,using only 14 records from the MIT-BIH database, the neural network-based classifier presented by Nashash reached a sensitivity of 98.1% and a positive predictive of 94.7%. A neural classifier of the PVC (Premature Ventricular Contraction) combined with the wavelet transformation and the temporal characteristic of the ECG was proposed by Inan. It obtained an accuracy of 85.20% on 40 records (Inan, 2006). Quiniou et al (Quiniou, 2006) proposed inductive logic programming, which is an automatic learning technique for chronicle recognition. Their system called CRS (Chronicle Recognition System), developed at France Telecom R & D Lannion, allows efficient processing of important event flows and chronic bases of consequent size.

Artificial Neuro Networks (ANN)

A neural network is a computational model whose design is very schematically inspired by the functioning of real neurons. Neural networks are generally optimized by statistical learning methods, so that they are placed on the one hand in the family of statistical applications, which they enrich with a set of paradigms allowing to generate large spaces functional, flexible and partially structured, and on the other hand in the family of methods of artificial intelligence which they enrich by making decisions based more on perception than on logical reasoning forms (Haykin, 1999).

Structure Of Artificial Neuro Networks (ANN)

There are three possible types of neurons, which are organized into disjoint subsets called layers (input layer, hidden layer, and output layer). A neuron is connected to another neuron with a connection, which functions as a unidirectional instant signal. Each connection between these neurons is associated with a quantity called the weight or binding force (Haykin, 1999) [Figure 1].

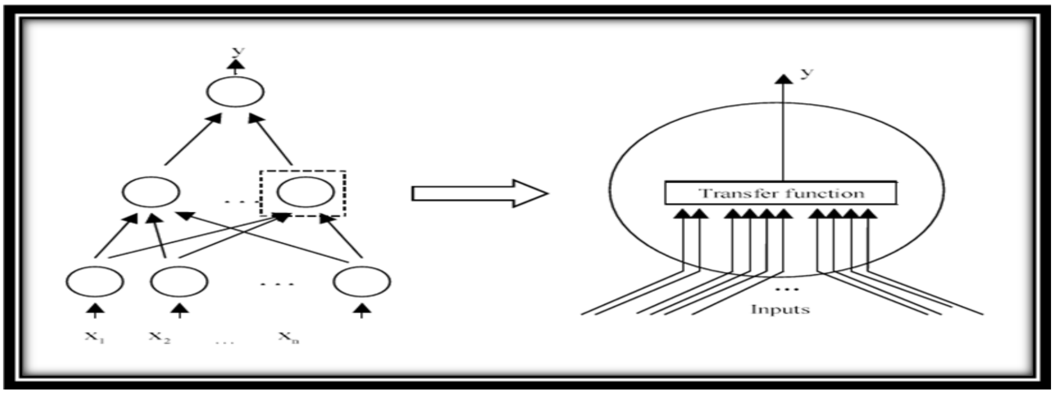

Figure 1: A network of neurons and its basic processing element.

First, the neuron computes an input network value by summing the input values multiplied by their corresponding weights. Then, the neuron determines the output value by applying a transfer function, which is generally a threshold function as a sigmoid. In addition, updates the weights of the neurons according to the procedure gained.
Input neurons behave differently from other neurons. Each of the input neurons receives exactly one input signal, which represents an element of an input configuration outside the network. Therefore, the neurons of the input layer thus have an input pattern for all output neurons. As a general rule, these neurons do not distribute signals to the neurons in the next layer (Haykin, 1999).

ECG Signal

In [Figure 2], we have the different waves of a normal ECG, in our study we are interested in the Ventricular case that can cause sudden death in a patient.

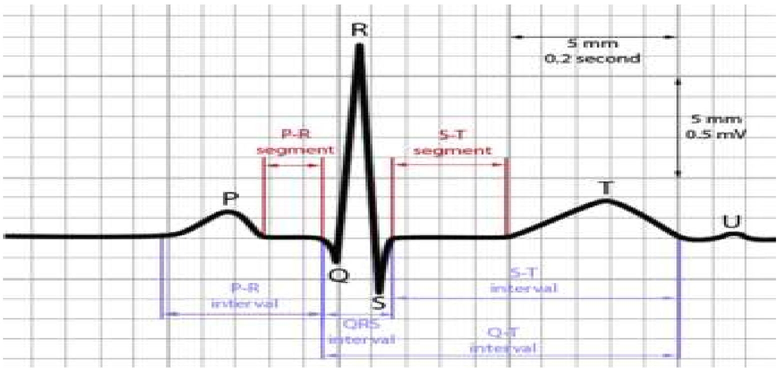

Figure 2: The different wave Electrocardiogram (ECG) signal.

Premature Ventricular Contraction (PVC)

Ventricular fibrillation is a cardiac rhythm disorder which manifests as a complete disorganization of the electrical activity of the ventricles with the immediate consequence of the loss of any effective cardiac contraction. According to (Briand, 2002) Ventricular fibrillation is characterized by the occurrence of very abnormal, widely varying, abnormally large, unequally amplitude ventricular complexes, occurring in a totally

irregular and high frequency manner (Talbi, 2011).
The parameters used to try to predict the risk of PVC are relative to the QRS and P waves of the ECG [Figure 3].

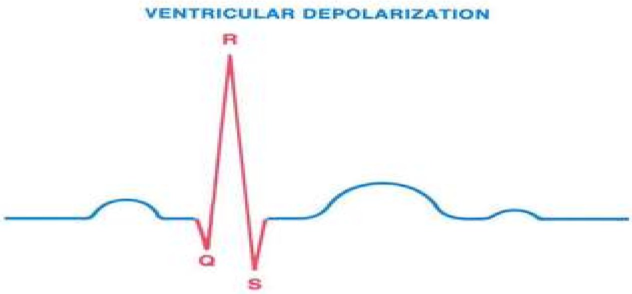

Figure 3: ECG of a subject which has premature ventricular contractions (PVC) (Talbi, 2011).

To discriminate between the two types of beats (normal and at risk (PVC)), it is imperative to calculate certain parameters and characteristics that can constitute the input vectors of the classifier. These feature vectors are each composed of 9 elements:
- The temporal parameters, namely the duration and the amplitude of the P wave represent the two first elements of the vector and the duration of the QRS complex.
- The shape of the QRS complex.

Experimentation

The ECG signals used in this work are the actual recordings of the database MIT-BIH. These signals are sampled at the frequency of 360 Hz. two American cardiologists have made annotations on these signals and who made the diagnosis for these recordings, and each cardiac cycle has been annotated by them. These parameters are essential for learning and classification evaluation.
The parameters used were calculated using an algorithm developed and implemented in the LTSI laboratory at the University of Rennes 1 France. This algorithm is based on the technique presented by J. Pan WJ Tompkins and (Pan et al, 1985) was applied to the MIT-BIH data base (MIT BIH, 1992).
The right choice of the parameters of the input vector classifier is very important. For this three-dimensional geometric data analysis is recommended to see the degree of membership of each parameter for each class (Normal, Ventricular, Other).

Parameters	Signification
1	*The moment of detection of the peak R*
2	*QRS onset*
3	*QRS offset*
4	*Last RR interval*
5	*Beat begin*
6	*Beat end*
7	*Iso electric level*
8	*Amplitude pic to pic*
9	*ST level*

Table 1: Parameters of MIT-BIH data base.

Methodologies

The multilayer perceptron (PMC) is the most widely used network. It is a feedforward network composed of successive layers. Each neuron of a layer receives signals from the previous layer and transmits the result to the next one, if it exists. Neurons of the same layer are not interconnected. A neuron can not therefore send its result that has a neuron located in a layer posterior to his. The orientation of the network is fixed by the single direction of propagation of information, of the input layer to the output layer. For the networks considered, the notions of input and output layers are therefore systematic. The latter constitute the interface of the network with the outside. The input layer receives the input (or variable) signals and the output layer provides the results. Finally, the neurons of the other layers (layers hidden) have no connection with the outside and are called hidden neurons.By convention, the input neurons always have an activation function (identity), letting the information pass without modifying it. As regards the output neuron, it may be associated with a linear or non-derivative activation function, which may or may not be derivable, depending on the nature of the problem to be solved. This type of network is very efficient for classification problems (Parizeau, 2004).

Architecture

The network designed for the classification of heart beats is Multi-Layer Perceptron (MLP) [Figure 4].
- The input vector X=[x1 x2 … x9] represents 9 parameters characterizing a heartbeat of the data base LTSI [Table 1], which have been linked to all neurons in MLP network, and gives a single output unit, which produces the variable Y.

- The external connections of the neuron i with the input vector S is materialized by a synaptic weight vector Mi = [mi1 mi2 …mi9] whose weights are assigned randomly to the top.

- Each neuron i of the map is related to all other neurons map: interaction between neurons. wik the internal connections of the neuron i with its neighbors are performed by assigning synaptic weights.

- This model realizes an application of Rp in R.
- The network architecture determined by the neuron connection scheme is a composition of elementary function and represents a family G (.W) of nonlinear functions and whose parameters are the weights of connections of the network W.

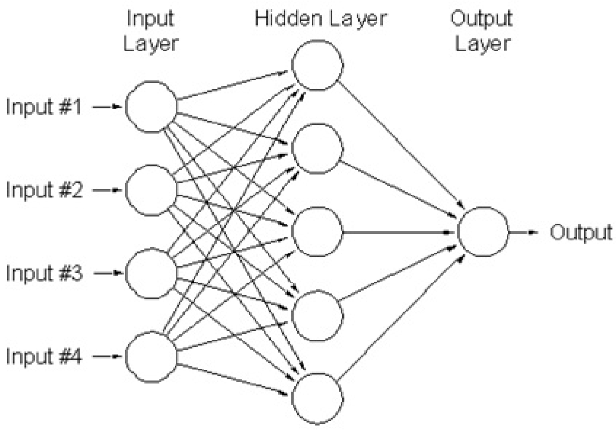

Figure 4: Multi-Layer Perceptron (MLP).

- The output of the network will have an expression of the following form depending on the number of layers which compose it :

$$Y = \sum_{i=1}^{n} W_i - f_i\Big(\sum_{j=1}^{p} W_{ij}.X_j + X_{i0}\Big) + W_0 \qquad (1)$$

- Estimating the weights of the MLP network involves least-squares minimization of the error (a cost function) defined on the learning basis. This error is given by:

$$E(\vec{W}) = \frac{1}{2} \times \sum_{examples} (cible - output)^2 \qquad (2)$$

Learning Network

A learning system takes as input a set of examples (cardiac cycles) from which it seeks a definition. In our case, the system seeks to learn the forms of cardiac arrhythmias from the examples provided at its entry from the MIT-BIH database.

These examples are presented in the form of parameters (elements of the input vector [Table 1]) which represent the temporal and morphological characteristics of the cardiac cycles classified according to the arrhythmias to which they correspond.

The learning algorithm-back propagation in this case-ensures that the classes produced allow to best discriminate the input examples.

Implementation Of The Classifier

The purpose of the software implementation of the classifier is to determine the size and parameters of the neural network, namely:

- Number of layers and number of neurons for each layer.
- Error reached.
- Number of iterations.

These settings provide the best network performance. We discuss in this section the conditions and method of learning, the database used the programming and the dimensioning of the network.

Experiment Results

The database used allowed the creation of two other databases: one for learning and the other for testing, which will be used for the training and evaluation of our classifier. The selected patients are given in the following table [Table 3].

Once the learning has been completed, it is necessary to test on another database different from that of the learning.

For the evaluation of our classification system, we used four statistical laws based on the recognition of mutual categories: Tp (True positive), Tn (True negative), Fp (False positive), Fn (False negative).

These laws are as follows:

The sensibility : $Se = Tp / (Tp + Fn)$, it is the fraction of real cases targeted correctly recognized on all the actual cases referred to.

The specificity: $Sp= Tn / (Tn + Fp)$, this is the fraction of actual non-target cases properly rejected.

The correct classification : $CC= (Tp + Tn) / (Tp + Tn + Fp + Fn)$, this is the correct classification rate.

The results presented in this study for the classification of ECG signals were obtained by applying to the classifier input ECG signals of "MIT BIH Arrhythmia Database". The sensitivity, specificity and classification rate are three parameters calculated for each signal to evaluate and compare the results obtained. The performance of the classifier is shown in [Table 3].

Our classification system allowed us to obtain a recognition rate of 94% by applying the set of ECG signals of MIT BIH Database with a specificity of 96.49% and a sensitivity of 94.60%. These performances were achieved mainly through:

Signals	Normal Beat	PVC Beat	SE	SP	CC
Patient 1	2272	2239	99	95.08	95.03
Patient 2	1864	1860	NAN	93.01	93.5
Patient 3	2186	99	100	100	100
Patient 4	2026	1506	97.01	97.05	97.01
Patient 5	2650	2423	86.03	84	84.02
Patient 6	2256	225	99.01	83.05	83.06
Patient 7	2601	1743	81.04	96.07	94.03

Table 3: Percentage recognition rate of the classifier.

Conclusion and Perspectives

In this article, we propose a system for the diagnosis of very common cardiac arrhythmias (PVC), based on neural networks MLP, which is responsible for determining the type of heartbeat according to its most representative characteristics. The learning algorithm was implemented under the Matlab environment. Tests carried out on a MIT-BIH database made it possible to achieve a classification rate close to 94%. The result is satisfactory as long as we have improved the performance of the classifier on the one hand and, on the other hand, a network that has a minimal architecture with respect to the number of classes in output. This point is very important because it allows minimizing the response time of the classifier if one wants to have a Reel time classifier.

Among the prospects of this work, the expansion of the database, and tried other methods of classification.

References

F.M. Ham, F.M. (1996). Classification of cardiac arrhythmias using fuzzy ARTMAP, *IEEE Transactions on Biomedical Engineering*, vol. 43, no. 4 ,(pp. 425-430).

Al-Nashash, H. (2000). Cardiac arrhythmia classification using neural networks. *Technology Health Care*, Sharjah, United Arab Emirates, (pp. 363-372).

Inan, O.T. & Giovangrandi, L. & Kovacs G.T.A. (2006). Robust neural network based classification premature ventricular contractions using wavelet transform and timing interval features, *IEEE Transactions on Biomedical Engineering*, (pp. 2507-2515).

Quiniou , R . & Cordier, M.O. & Fromont, E. & Portet, F. (2006). Apprentissage multisource par programmation logique inductive , 15e congrès francophone AFRIF-AFIA Reconnaissance des Formes et Intelligence Artificielle, Tour, France.

S. Haykin. (1999). Neural networks a comprehensive foundation, prentice hall international, second edition, (pp 34-78).

Briand,F. & Bassand. J. P. (2002). http://www.besancon-rdio.org/cours/35-tachyven-cli.php#00.

Talbi, M.L. (2011). Analyse et traitement du signal electrocardiographique (ECG), *doctoral thesis*, *University of Constantine*, Algéria.

Pan, J. & Tompkins. W.J. (1985). A real-time QRS detection algorithm, IEEE Transactions on Biomedical Engineering, (pp. 230-236).

MIT BIH Arrhythmia database directory (1992). Third edition, *Harvard MIT Division of Health Sciences and technology*, *Biomed. Eng. Center*.

Parizeau, M. (2004). réseaux de neurones , GIF-21140 et GIF-64326,*Université LAVAL.*

