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Phonocardiogram and Electrocardiogram Signals Processing using Wavelet Transform and Multilayer Perceptron Neural Network

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ABSTRACT: This article deals with an original approach of acquiring and processing electrocardiogram (ECG) and phonocardiogram (PCG) signals for the diagnosis of cardiac arrhythmias in order to remedy the difficulties encountered with the ECG. Indeed, it integrates an analysis tool based on wavelet transforms for the characterization of ECG signals and a classification system from multilayer perceptron neural network of five categories of cardiac arrhythmias: normal (N), left bundle branch block (LBBB), right bundle branch block (RBBB), premature atrial contraction (PAC) and premature ventricular contraction (PVC). The digitization of the signals is made from an Arduino Mega 2560 board. The realized system has been tested on 6 patients and the results are visualized on a smart phone turning under android operating system. These results are in agreement with medical previsions. Recognition rates are as follows: 100% for class N, 100% for class LBBB, 75% for class RBBB, 90.9% for class PVC and 100% for class PAC. We obtain a generalization rate of 92.9%.

KEYWORDS: Electrocardiogram (ECG), Phonocardiogram (PCG), Cardiac arrhythmias, Multilayer perceptron neural network, Wavelet transforms.

I. INTRODUCTION

Cardiovascular diseases represent 29% of deaths worldwide [1]. Consequently, the prevention and clinical diagnosis of the various causes of the resulting deaths are of major importance. On one hand, the rise in the fields of electronics and computer science has encouraged the emergence of new approaches to information processing in order to produce a medical diagnosis. This development in the field of computer science has given rise to new approaches such as wavelet transforms for characterization and neural networks for classification and final medical diagnosis. On the other hand, the observation of the functioning of the heart over the long term produces an increased volume of data that can be difficult to analyze and easily lead to a misdiagnosis by a physician. This is why we must find new approaches to objective analysis of the cardiac signal. The images below show the phonocardiogram (fig 1.a) and electrocardiogram (fig 1.b) signals. Those curves translate respectively the mechanical and the electrical activity of the heart. B1, B2, B3 and B3 constitute the main parts of our PCG signal. For a normal heart, B1 and B2 are clearly audible. They have a sound resemblance with the onomatopoeias « *toum-tac* ». B3 and B4 correspond to noise of blood during the ejection and the opening of the sigmoid valves. For an ECG signal, we have the waves P, Q, R, S and T. Observation and analysis of that waves informs about the health of our heart.

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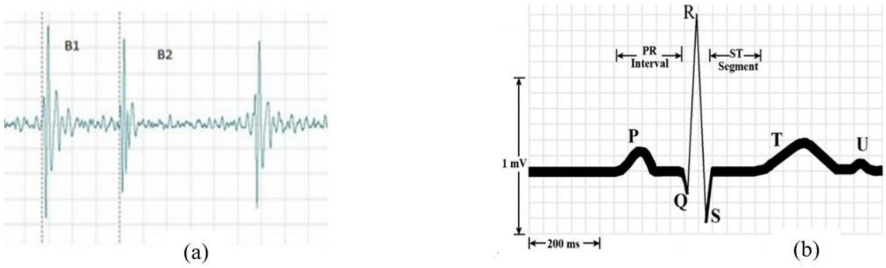

Fig 1: (a) Normal PCG signal, (b) Normal ECG signal

Regarding the ECG signal, the main information that provides precisions about the quality of the cardiac signal is contained in the QRS complex. This is the most pronounced feature visible on an ECG. Various methods based on wavelets are proposed in the literature to extract the main information. Among the most widely used are the Haar wavelets [3, 4], the Mexican hat [5, 6], the Morlet wavelets [7, 8], the quadratic spline wavelets [9] and even their combination [10]. In [11], the authors propose an algorithm for the detection of the QRS complex for an ECG signal containing the EMG frequencies. They obtain results equivalent to those highlighted in [12, 13]. The detection of the QRS complex by using the Haar discrete transformation has been presented in [14]. This algorithm achieves a correct classification rate of 95.74% on 5 records from patients. Dinh et al. [15] use the cubic spline wavelets for the detection of the QRS complex. They get an average error of 0.75%. Alvarado et al. [16] consider the continuous wavelet transform for the characterization of the QRS complex. This approach is tested on eight 30-minutes records from the MIT-BIH database. It leads to an error rate of 0.47%. Finally, the authors of [17] consider the non-stationary nature of the QRS complex for the detection of R peaks and propose an approach combining the Hilbert transformation in combination with a sliding averaging filter. They obtain a classification rate of 99.80% on 48 recordings of the MIT-BIH signal base. The use of wavelet transform process based on quadratic wavelets for identifying individual ECG waves has been proposed by Gutiérrez et al. [18]. After the identification of ECG waves, the results are transferred to a classifier process. Numerous processes have been used in the literature. For instance, the authors in [19] use a multilayer, 3-input neuron, feedforward artificial neural network trained with supervised backpropagation; the results are better than those obtained using multiple regression analysis. The use of RR-interval for arrhythmia classification has been presented in [20]. The method of multilayer perceptron artificial neural network has been developed and compared with linear discriminant analysis in [21].

II. MATERIAL AND METHOD

In this section, we describe the design phase of the various cardiac signal acquisition circuits developed in this study. The operating diagram is illustrated in the following figure.

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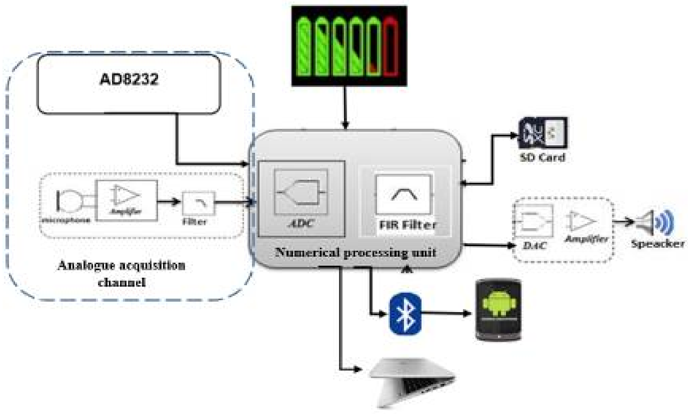

Fig 2 : Operating diagram

A. MATERIAL

The material used in our work consists of:

- An electret condenser microphone for capturing PCG signals;
- A TDA 2822 for amplifying and listening to cardiac sounds;
- The AD8232 for the acquisition of the ECG signal;
- An ATMEGA 2560 microcontroller card for digitizing cardiac signals from the analogue acquisition stage;
- An Arduino shield SD for saving digitized signals;
- A Bluetooth module HC06 for sending data to the smartphone;
- An Android smartphone for viewing different curves;
- A PC for the characterization and classification of ECG signals.

B. Methods

II.B.1 PCG Acquisition

The acquisition of the PCG signal is done by means of an electret condenser microphone. It is a circuit whose frequency range is between 20 and 20,000 Hz. It has been chosen with regard to the characteristics of the following microphones:

Table 1: Comparison of microphone characteristics

Type of microphones	Electret Condenser Microphone (ECM)	Dynamic	Piezoelectric	Preference
Cost	Low	Low	High	ECM/ Dynamic
Sensitivity	Good	Low	Good	ECM / Piezo
Dimension	Small	Big	Small	ECM / Piezo
Frequency band	20 Hz – 20 kHz	50 Hz - 20 kHz	10 Hz - 20 kHz	ECM / Piezo

The acquired signal of the microphone is filtered by means of a band pass filter of order 2 by cascading a high-pass filter and a low-pass filter whose cut-off frequencies are respectively 20 and 994.718 Hz. The signal from the acquisition stage is digitized using the Arduino board and transmitted via Bluetooth to the smartphone for its visualization. This is an illustration in fig 3.

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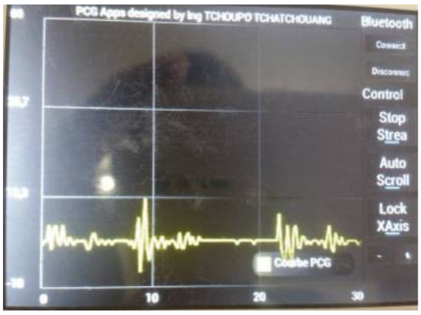

Fig 3: PCG Signal of a patient

II.B.2 ECG Acquisition

For ECG signal acquisition, we use the AD8232. It's an integrated signal conditioning block for ECG. Its role is to extract, amplify and filter small bio potential signals in the presence of noisy conditions, such as those created by motion or remote electrode placement. This design allows for ultralow power analog-to-digital converter (ADC) or an embedded microcontroller to acquire the output signal easily. The AD8232 can implement a two-pole high-pass filter for eliminating motion artefact and the electrode half-cell potential. This filter is tightly coupled with the instrumentation architecture of the amplifier to allow both large gain and high-pass filtering in a single stage, thereby saving space and cost.

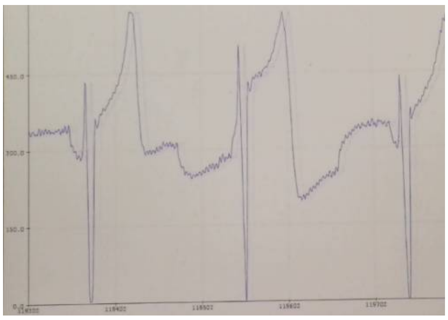

Fig 4: ECG signal of a patient

II.B.3 ECG SIGNAL PROCESSING

There are two main steps in ECG signal processing. The first is pre-processing, which consists of filtering and standardizing data. The second consists in the characterization of the signal using the wavelet method to obtain the inputs of our neural classifier.

a. PREPROCESSING

The ECG signal contained in the learning base is subjected to various frequency interferences. It is more precisely the frequencies of the electromyogram, that is to say the movement of the muscles, the sector and its harmonics, artifacts due to the movement of the patient or the bad contact of the electrodes. In order to eliminate the frequencies of the electrical network, we have implemented a Butterworth-type digital band-pass filter with cut-off frequencies of [49.2 - 50.8] Hz. For baseline corrugations, we used a Butterworth type high pass filter with a cut-off frequency of 0.8 Hz.

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Once the preprocessing has been carried out, it is important to normalize the signal to reduce the calculation time in the rest of the process. To do this, the average value is taken from each sample in order to eliminate the offset effect. Subsequently, we divide by the maximum.

b. CHARACTERIZATION OF ECG SIGNAL

In this work, we rely on the wavelet packet transformation proposed by Coifman and Wicker Hausser. The principle is to generate from a mother wavelet a library of base wavelets. Each of these bases provides a unique representation of the original signal. This library is constructed by decomposing the spaces of the approximations and that of the details. This algorithmic approach is illustrated in the following figure.

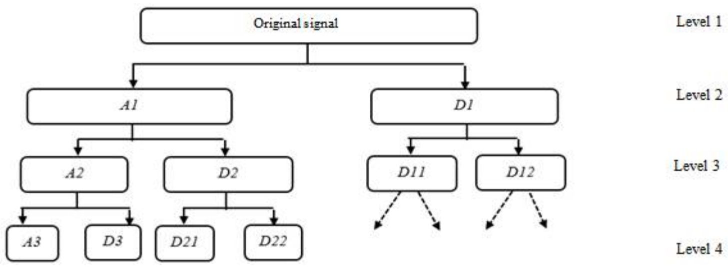

Fig 5 : Wavelet packet decomposition

- **DETECTION OF R PEAKS**

The detection of R peaks 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 step. In order to detect the R peaks, the details specific to the QRS complexes will be selected. Eight wavelet decomposition levels are performed on the pre-processed ECG signal using the db4 wavelet. Details D3 to D6 are retained and all others are deleted. The reconstruction of the signal is thus carried out from the preserved details. This makes it possible to keep the QRS complex in the signal obtained and to eliminate the other low and high frequency components. The signal obtained is squared in its positive part to accentuate the R wave and attenuate the other waves. Adaptive thresholding is performed to detect the R peak.

- **DETECTION OF Q AND S WAVES**

After the detection of R peaks, Q and S must be identified to locate the QRS complex. In general, Q and S waves have a small amplitude but a high frequency and their energy are mainly small scale. To show them, we keep only the details D5 to D7 for the reconstruction of the signal. Moreover, Q and S are negative deflections which occur on either side of the peak R over a maximum interval of 0.1 second. Q being located on the left is considered as the minimum amplitude that precedes the peak R and S to the right is the maximum amplitude that follows it.
The P and T waves are also detected according to the same principle. Practically, we are interested in the details D6 and D7 followed by a thresholding to discriminate the two types of waves. After the detection of the different waves P, Q, R, S and T, we determine the set of morphological criteria that constitute a part of the inputs of our neural model: PQ, ST, PR, QS, RR, the width of the QRS complex, its amplitude and the ratio $\frac{RR_S}{RR_P}$.

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In order to increase the discrimination rate of our classifier, we have also computed the following parameters by means of the wavelet transformation: The minimum, maximum, mean, mode, covariance, variance, standard deviation, entropy, energy density, entropy according to Shannon. The principle is described in the following flowchart:

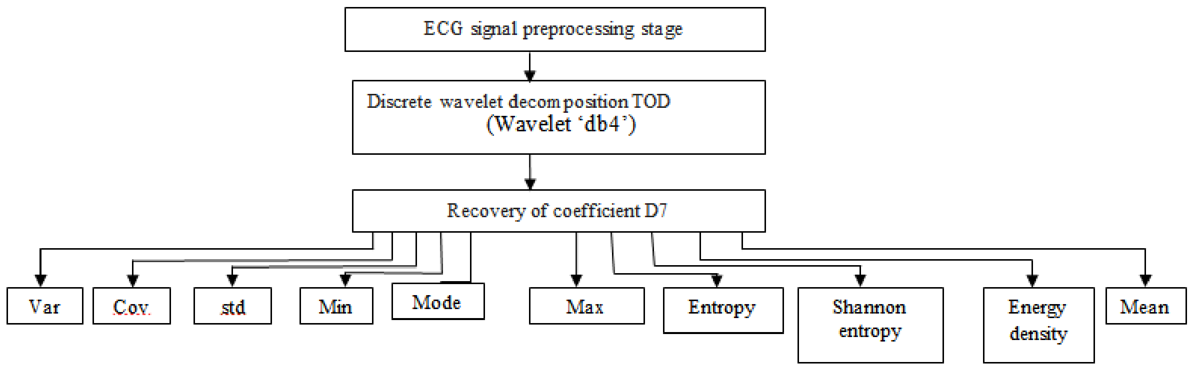

Fig 6: Principle of the algorithm for extracting statistical parameters

The set of computed elements constitute the elements of the input vector for the characterization, learning and classification of ECG signals for the diagnosis.

II.B.4 ECG SIGNAL PROCESSING

For the final classification, we used a multilayer perceptron neural network. The number of neurons in the input layer is fixed relative to the number of elements of our vector. In this study, we opted for 19 elements of discrimination which thus constitute the size of our input vector. The size of the output vector corresponds to the number of different classes of pathologies. In our case, we used 5 cardiac arrhythmias: N, LBBB, RBBB, PVC and PAC. After several tests, we selected a choice of 12 neurons as a component for the hidden layer.

III. EXPERIMENTAL PROTOCOL

The MIT-BIH database is a reference base for the automation and validation of algorithms for the processing of certain physiological signals. It contains a very wide variety of physiological signals among which 48 ECG records lasting between 1 and 30 minutes. These records were obtained on the DII and V5 routes. It was collected by a group of researchers, to be used for the validation and comparison of algorithms for the automatic diagnosis of cardiac pathologies to name but a few. Each recording is sampled at a frequency of 360 Hz. The main advantage of this database is that it contains all the pathologies targeted in this work. These records correspond to patients divided into two groups of both sexes, comprising 25 males aged between 32 and 89 years and 22 females in the age range 23 to 89 years. The signals numbered from 100 to 124 for the first group comprise a variety of waveforms and from 200 to 234 for the second group which corresponds to a variety of pathological cases. Each record was evaluated independently by several cardiologists to ensure a certain reliability of the results. Twenty-eight base-level signals were used to help us in the tasks of learning, testing and validating the implemented method.

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Table 2: MIT-BIH database records

Class of heartbeat	N	LBBB	RBBB	PVC	PAC
Records	MIT-100 MIT-103 MIT-105 MIT-108	MIT-112 MIT-113 MIT-114 MIT-117 MIT-115	MIT-109 MIT-111 MIT-207 MIT-214	MIT-118 MIT-124 MIT-212 MIT-232 MIT-231	MIT-106, MIT-200, MIT-119 MIT-214, MIT-203, MIT-208 MIT-209, MIT-213, MIT-220 MIT-202

IV. EXPERIMENTAL RESULTS

Our algorithm was tested on the MIT-BIH signal base records and on six patients. We obtained the following confusion matrix at the end of our various tests:

Fig 7: Confusion matrix

From this confusion matrix generated by Matlab:

- Output class corresponds to the result given by the neural network once implemented;
- Target class is the expected result;
- On the diagonal, we observe the correct classification rates of each class studied and the number of elements correctly classified.

On output, the correct classification rate is shown in green, and the invalid classification rate of each sample per class is shown in red. The first class corresponds to the normal class, the second to the left bundle branch block, the third to the right bundle branch block, the fourth to the premature ventricular contraction and the fifth to the premature atrial contraction. From the resulting confusion matrix, we observe that the unidentified normal beats are designated by our classifier as right bundle branch blocks and premature ventricular contraction. As for the rest, no beating is classified outside its category. This situation reinforces the credibility of the choice of the 19 parameters used in the characterization of the heartbeat. In order to better choose the retropropagation function of the error to be used for the

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learning phase, we carried out a comparative study. First, we have listed all the retropopagation functions present in the toolbox and we have evaluated the performance of each of them. These various algorithms are listed in Table 3.

Table 3: Matlab retropropagation functions

trainlm	Levenberg-Marquardt backpropagation
trainbfg	BFGS quasi-Newton backpropagation
traingda	Gradient descent with adaptive learning rate backpropagation
traingdx	Gradient descent with momentum and adaptive learning rate backpropagation
traingd	Gradient descent backpropagation
trainrp	Resilient backpropagation
trainscg	Scaled conjugate gradient backpropagation
traincgp	Conjugate gradient backpropagation with Polak-Ribiére updates
traincgf	Conjugate gradient backpropagation with Fletcher-Reeves updates
traincgb	Conjugate gradient backpropagation with Powell-Beale restarts
trainoss	One-step secant backpropagation
trainbr	Bayesian regulation backpropagation

The *trainbr* function is the one for which we have obtained the best rate of generalization. For the evaluation of the performance and quality of the neural network classification, we determined the sensitivity for each type of class represented.

Table 4: Sensitivity of the proposed method for each class

Evaluation parameter	Beat type	Value (%)
Sensitivity	Normal	100
	LBBB	100
	RBBB	75
	PVC	90.9
	PAC	100
Correct classification rate		92.9

Our results have been compared with those of the literature in the following table:

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Table 5: Comparison of our results with those of the literature

Author	Processing method	Feature classification	Classification accuracy
This work	Wavelet Transform and Multilayer Perceptron Neural Network.	5 heartbeats	92.90 %
Jose Antonio Gutierrez et al. [18]	Wavelet Transform and Probabilistic Neural Network.	8 heartbeats conditions	92.75 %
Ebrahimnezhad et al. [22]	Linear predictive coefficients and Probabilistic Neural Network.	4 heartbeats conditions	92.90 %
Tsipouras et al. [23]	Collection of Digital Signal Processing methods.	4 heartbeats conditions	94% (arrhythmic episode) and 98 % (arrhythmic beat classification)
Homaeinezhad et al. [24]	Wavelet transform and Fuzzy inference classification (FCM clustering).	QRS geometrical complex	94.58 %
de Chazal et al. [26]	Collection of Digital Signal Processing methods.	5 heartbeats conditions	Multiple reports, overall 96.4 %
Lin et al. [27]	Wavelet Transform and Probabilistic Neural Network.	7 heartbeats conditions	97% (High) classification rate for a single arrhythmia, decreases when signals contain multiple arrhythmias
Homaeinezhad et al. [28]	Wavelet transform and Fuzzy inference classification (Subtractive clustering).	QRS geometrical complex	97.41 %
Yu et al. [29]	Wavelet Transform and Probabilistic Neural Network.	6 heartbeats conditions	99.65 %

V. CONCLUSION

Throughout this work, an original method of acquisition and processing of electrocardiogram (ECG) and phonocardiogram (PCG) signals for the diagnosis of cardiac arrhythmias has been presented. For the PCG signal, the acquisition has been performed by means of an electret condenser microphone. The signal obtained has been visualized on a smart phone turning under android operating system. For the ECG signal, the approach consisted of an analysis tool based on wavelet transforms for the characterization of ECG signals and a classification system from multilayer perceptron neural network of five categories of cardiac arrhythmias: normal (N), left bundle branch block (LBBB), right bundle branch block (RBBB), premature atrial contraction (PAC) and premature ventricular contraction (PVC). Our confusion matrix showed a classification rate of 92.9 % which is a promising result. The recognition rates obtained for the different arrhythmias were: 100% for N, 100% for LBBB, 75% for RBBB, 90.9% for PVC and 100% for PAC. It would be interesting to extend the present approach to the recognition of other arrhythmias like: auricular fibrillation, sinoauricular heart block and supraventricular tachycardia.

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