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Ischemia classification via ECG using MLP neural networks

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Abstract

This paper proposes a two stage system based in neural network models to classify ischemia via ECG analysis. Two systems based on artificial neural network (ANN) models have been developed in order to discriminate inferolateral and anteroposterior ischemia from normal electrocardiogram (ECG) and other heart diseases. This method includes pre-processing and classification modules. ECG segmentation and wavelet transform were used as pre-processing stage to improve classical multilayer perceptron (MLP) network. A new set of about 800 ECG were collected from different clinics in order to create a new ECG Database to train ANN models. The best specificity of all models in the test phases was found as 88.49%, and the best sensitivity was obtained as 80.75%.

Keywords: Classification, ECG, ischemia, MLP, DWT.

1. Introduction

The Ischemic Heart Disease (IHD), also known as Coronary Artery Disease, is a condition that affects the supply of the blood to heart. The heart muscle depends on the coronary arteries for the supply of oxygen and nutrients, and only the inner layers (endocardium) profit from the oxygen rich blood that is being pumped. Treatment and complications of an inferior wall infarction is different than those of an anterior wall infarction. An inferior wall infarction may cause a decrease in heart rate because of involvement of the sinus node. Nevertheless, the anterior wall performs the main pump function, and alterations of the function of this wall will lead to decrease of blood pressure, increase of heart rate, shock and on a longer term heart failure. So, long term effects of an anterior wall infarction are usually more severe than those of an inferior wall infarction.

The heart receives oxygen and nutrients through the right and left coronary arteries. As shown in Fig. 1, the left coronary artery (LCA), which arises from the aorta above the left cusp of the aortic valve, divides itself in the left anterior descending artery (LAD) and the left circumflex artery (LCX, or ramus circumflexus - RCX). This artery supplies the left atrium, part of the right atrium, left third of the anterior wall of the right ventricle, left ventricle (except right half of lower side), and anterior two-thirds of the interventricular septum.

The right coronary artery (RCA), which originates above the right cusp of the aortic valve, connects to the ramus descendens posterior (RDP). This artery supplies the right atrium, the inferior wall, the ventricular septum, and the posteromedial papillary muscle. This one usually also supplies both nodes (sinoatrial node and atrioventricular node).

The early diagnosis of IHD is very important to minimize myocardial cell damage and initiate appropriate treatment, moreover, IHD is so dangerous than it is the most common cause of sudden death in different countries around the world. The occluded coronary can be identified with aid of ECG.

Electrocardiography expresses heart electrical activity, so diseases could be diagnosed by morphological study of recorded data. Cardiologist commonly use this technique since it consists of effective, non-invasive, and low-cost tool to the diagnosis of cardiovascular diseases. For this purpose, ECG record is made to examine and observe a patient. Early detection and treatment of the heart diseases can prevent permanent damages on tissues of the heart.

In this study, the standard 12-lead ECG has been used in order to record the clinical information of each patient. The term 'lead' refers to the tracing of the voltage difference between two of the electrodes, namely, I, II, III, aVL, aVR, aVF, V1, V2, V3, V4, V5, and V6. However, the first six leads are a linear combination, so only two of them are enough to gather all necessary information for analysis. (1)

The most representative sign of myocardial ischemia is ST segment elevation or depression in two contiguous leads, in acute infarction, and pathological Q waves (high voltage), in chronic infarction. (2)

There are a few approaches for computer processing of ECG for diagnosing certain heart diseases. The two main used strategies are methods based in morphological analysis (3) (4) (5) and methods based in statistical models (6) (7) (8). A third group, methods based in artificial neural networks (ANN) (9) (10) (11), is being developed lately focusing in ECG signal classification.

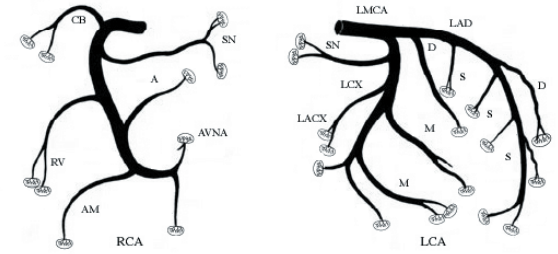

Fig. 1. Coronary arteries

Several techniques have been applied to ECG for feature extraction, such as Discrete Cosine Transform(DCT) (12), Discrete Fourier Transform (DFT) (13), Continuous Wavelet Transform (CWT) (14), Wavelet Transform (DWT) (15), Principal Component Analysis (PCA) (16), and Multidimensional Component Analysis (MCA), among others.

Artificial neural network (ANN) are being used in a wide variety of applications, such as classification tasks or pattern recognition. Multilayer perceptron (MLP) is a traditional ANN model, in which each neuron computes the weighted sum of its inputs and applies to sum a nonlinear function called activation function (Fig. 2).

The perfomance of MLP depends mainly on the learning algorithm, the number of hidden layers, the number of hidden neurons, and the activation function for each neuron. The commonly investigated activation function in literature is sigmoid function, which is fixed and cannot be adjusted to adapt to different problems, but it is critical in the performance of MLP. This function represents the neuron response: a relation between a single input, the weighted sum, and a single output. MLP and Radial Basis Function (RBF) have shown very good learning and predicting capabilities in the classification question. (17) (18) (19)

In this study we propose a two stage system for ischemia detection. The first stage is responsible for signal enhancement and feature extraction using the signal averaging and wavelet transform. For the classification stage we opted for the MLP.

This paper is divided into six sections, following this initial introductory section (Section 1), the basis of the employed signal processing will be commented (Section 2), and the most important details of the new ECG database used will be discussed (section 3). Next the pre-processing stage (Section 4) and classification stage (Section 5) will be described. And finally, the results (Section 6) and conclusion (Section 7) of the study will be explained.

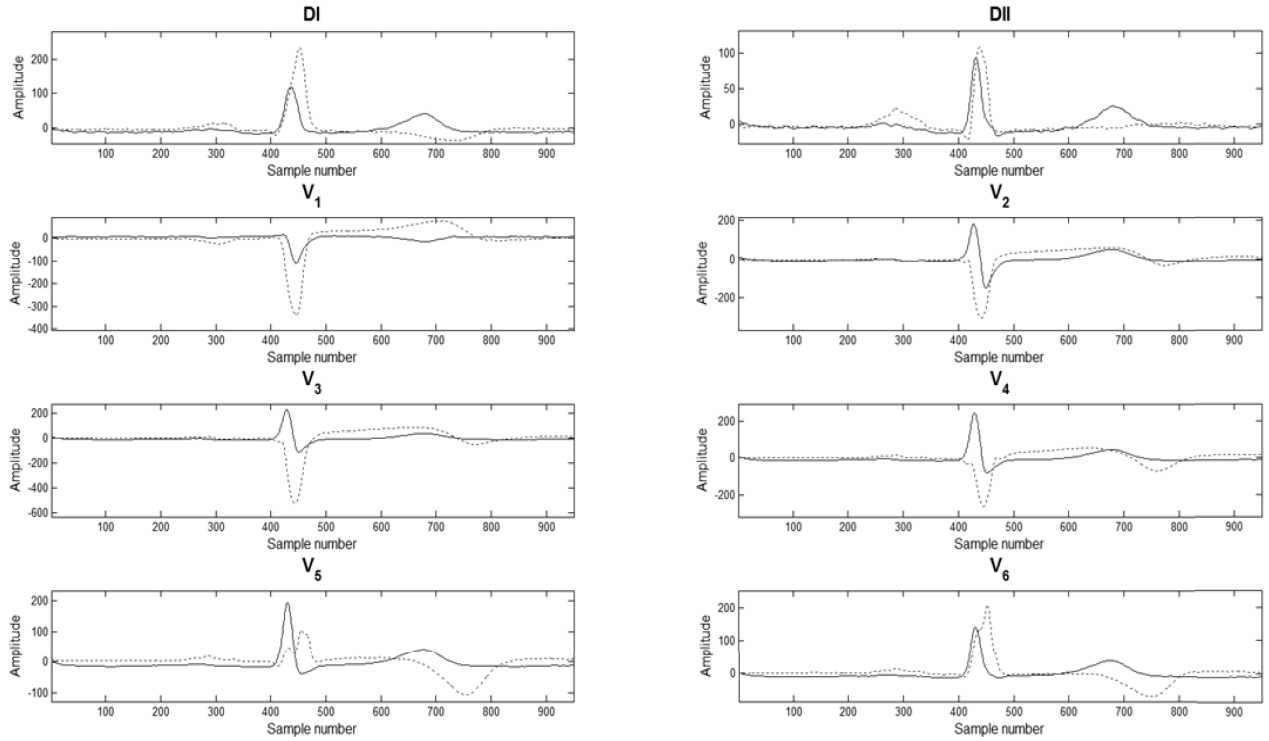

Fig. 3. Healthy patient (solid line) vs. patient with extensive anterior ischemia (dotted line) [Gem-Med ECG DB]

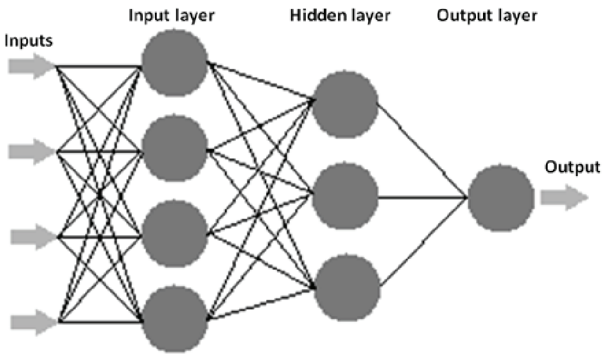

Fig. 2. ANN: Basic Multilayer Perceptron

2. Background

2.1. *Continuous wavelet transform*

Since 1982, when Jean Morlet proposed the idea of the wavelet transform, many people have applied the wavelet to different fields, such as noise suppression, image compression or molecular dynamics. Wavelets are a family of functions generated from translations and dilatations of a fixed function called the ‘‘mother wavelet”. The wavelet transform can be thought of as an extension of the classic Fourier transform, but it works on a multiscale basis (time and frequency). The wavelet transform can be classified as continuous or discrete. Many researchers (Daubechies, Haar, Meyer, Mallat, etc.) enhanced and developed this signal-processing tool to make it more efficient. (20)

The wavelet analysis has been introduced as a windowing technique with variable-sized regions. Wavelet transforms may be considered forms of time-frequency representation for continuous-time signals, and introduce the notion of scale as an alternative to frequency, mapping a signal into a time-scale plane. This is equivalent to the time-frequency plane used in the STFT (short time Fourier transform). Each scale in the time-scale plane corresponds to a certain range of frequencies in the time-frequency plane. A wavelet is a waveform of limited duration. Wavelets are localized waves that extend for a finite time duration compare to sine waves which extend from minus to plus infinity. The wavelet analysis is the decomposition of a signal into shifted and scaled versions of the original wavelet whereas the Fourier analysis is the decomposition of a signal into sine and cosine waves of different frequencies. The wavelets forming a continuous wavelet transform are subject to the uncertainty principle of Fourier analysis respective sampling theory, so one cannot assign simultaneously an exact time and frequency response scale to an event.

Mathematically, the continuous wavelet transform of a function is defined as the integral transform with a

family of wavelet functions: in other words, the continuous wavelet transform (CWT) is defined as the sum of the signal multiplied by scaled and shifted versions of the wavelet function. A given signal of finite energy is projected on a continuous family of frequency bands of the form [f, 2f] for all positive frequencies. This frequency bands are scaled versions of a subspace at scale 1. This subspace is in most situations generated by the shifts of the mother wavelet Ψ(x). The projection of a function f (t) onto the subspace of scale a has the form:

$$W_f(a,b) = \frac{1}{\sqrt{a}} + \int_{-\infty}^{\infty} f(t)\Psi\left(\frac{t-b}{a}\right)dt \qquad (1)$$

For the continuous wavelet transform, the pair (a, b) varies over the full half-plane, while for the discrete wavelet transform this pair varies over a discrete subset of it.

2.2. *Discrete wavelet transform*

The discrete wavelet transform captures both frequency and time information as the continuous wavelet transform do, but using wavelets discretely sampled. The Fast Wavelet Transform (FWT) is an alternative to the conventional Fast Fourier Transform (FFT) due to it can be performed in O(n) operations and it captures as the notion of frequency content of the input (different scales - a) as the notion of temporal content (different positions - b).

As shown in Fig. 4, the DWT can be implemented by a series of filters. First the samples (s[n]) are passed through a low pass filter with impulse response l[n] resulting in a convolution of the two, and simultaneously, the samples are passed through a high pass filter with impulse response h[n] (Eq.2).

$$\begin{aligned} Y_{low}[n] &= (s * l)[n] = \sum_{k=-\infty}^{\infty} s[k]l[[n-k] \\ Y_{high}[n] &= (s * h)[n] = \sum_{k=-\infty}^{\infty} s[k]h[[n-k] \end{aligned} \qquad (2)$$

According to Nyquist's theorem, half of the frequencies of signal have now been removed, so half the samples can be discarded downsampling by 2 the outputs of the filters.

Calculating wavelet coefficients at every possible scale would waste computation time, and it generates a too large volume of data. However, only a subset of scales and positions are needed, scales and positions based on powers of two, so-called dyadic scales and positions. Then, the wavelet coefficients c_{jk} are given by (Eq. 3).

$$c_{jk} = W_f(2^{-j}, k2^{-j}) \qquad (3)$$

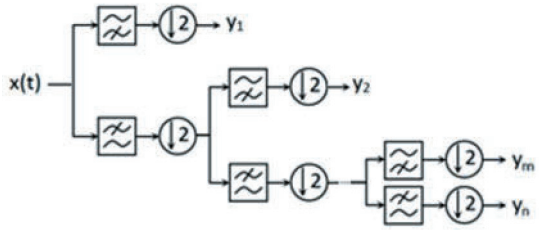

Fig. 4. Filter bank representation

where $a = 2^{-j}$, called the dyadic dilation, and $b = k2^{-j}$, is the dyadic position.

Such an analysis from the discrete wavelet transform (DWT) is obtained. DWT works like a band pass filter and DWT for a signal several levels can be calculated. Each level decomposes the input signal into approximations (low frequency part of initial signal) and details (high frequency part of initial signal). The next level of DWT is done upon approximations. In Fig. 4, y_1 corresponds to the first level of DWT (approximations - low pass filter), y_2 corresponds to the second level of DWT (approximations from details of first level), and so on. The penultimate level (y_m) corresponds to the approximations of the last filter pair, and the last level (y_n) corresponds to the details of the last filter pair. (21)

3. Database

A new ECG database was created by Gem-Med, S.L. The Gem-Med database contains eight lead ECG signals of about 800 patients. It is possible to recuperate all the 12 leads from the datasets recorded (I and II leads, and the six precordial leads V1 to V6) (1). These ECG signals are sampled at a frequency of 1.000 Hz and filtrated with a band-pass filter of 0.5 Hz and 45 Hz to correct the baseline and to suppress interferences (motion artefact, power line interference, etc.). Among the ECG which composed the new database, there are several diagnosis such as healthy patient, different types of bundle branch blocks (RBBB, LBBB and hemiblocks), different types of ischemias (inferior, lateral, superior, anterior, septal, chronic, acute, etc.), and so on.

Cardiologists have diagnosed each pathology with four possible results, namely, Sure, Probable, Discarding, or Negative. Those ECG showing unequivocal signs of the disease under study are marked as Sure. If a marker was not clear, or does not appear, the ECG is marked as Probable. When there is only a sign but cannot guarantee the diagnosis is marked as Discarding.

Finally, ECG which do not show any sign associated with the pathology under study are marked as Negative.
The original data is saved in SCP-ECG format, which stands for Standard Communications Protocol for Computer Assisted Electrocardiography. The ECG signals for training dataset contain eight lead of patients diagnosed with ischemia (Sure and Probable degrees) and those which were not diagnosed with this pathology. This dataset were divided into three groups of training, validation and testing. Each ECG database record is composed of several beats and all the eight leads. After the pre-processing block, the mean beat is calculated and the number of final variables is reduced to about 20 samples per lead. Each subnet works with a different pre-processing, so each one manages a different number of samples as input. The input data stores all the required leads concatenated in a one-dimensional vector.

4. Signal pre-processing

ECG signal pre-processing (Fig. 5) is performed in order to remove noise distortion (mean beat), to extract main features (wavelet transform) (22), and for data reduction (downsampling).

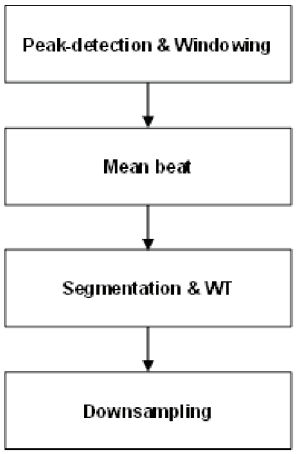

Fig. 5. Preprocess module

Firstly, as the QRS complex is the most prominent wave in ECG, R wave is recognized in each beat with a peak-detection algorithm. A window of 950 samples centered in the R wave is defined (Fig. 6). Except in cases of severe bradycardia or tachycardia, complete heart cycle falls within that window and all the significant points are approximately at the same sample number. Locating R-wave at the centre of the exploration window is achieved that variations in heart rate increases or decreases number of isoelectric line samples at the edges of the exploration window.
When all the beats are recognized, those that differ more are discarded (artefacts, extra systoles, etc.) and the rest are averaged in order to remove noise distortion. As in this work the diseases targeted are different kinds of ischemia, beat average do not suppress any relevant information as in other heart diseases like arrhythmias or some bundle branch blocks.

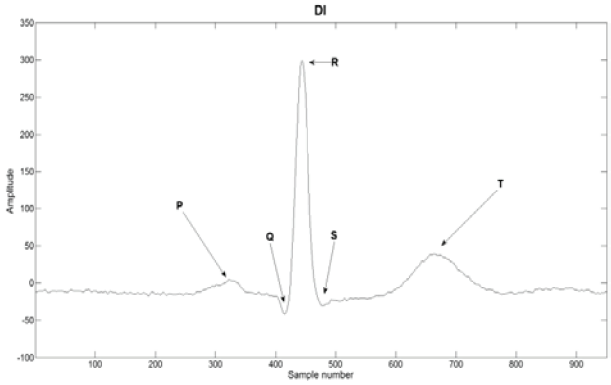

Fig. 6. ECG significant points

As prognostic factors for ischemia are mainly located in the QRS complex and T wave (2), before the feature extraction stage proceeds to segment the ECG signal. As mentioned previously, except in cases of severe bradycardia or tachycardia, by placing the R wave at a specific position, the QRS complex and T wave maintain their lengths and can be extracted by a windowing technique.
In this work, the Wavelet transform was selected in order to reduce the remaining number of samples. It is also essential to notice that determination of DWT level and the mother wavelet are very important in ECG feature extraction.
In this study the best results of ECG signals classification were obtained for DWT–MLP structure by examining different, already most used mother wavelets to select the best for DWT techniques, Also, optimal decomposition level parameter in DWT were specified empirically. Further we compared different six mother wavelets, namely, Haar, Daubechies 2, Daubechies 4, Coiflet 1, Symlet 2, Symlet 4, and a non DWT process.

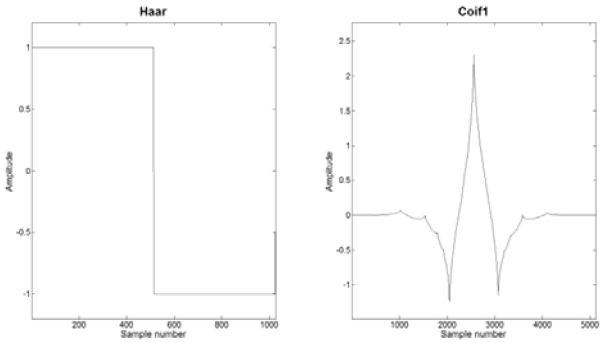

Fig. 7. Haar and Coiflet 1 mother wavelets

The Haar wavelet (Fig. 7) is the simplest possible wavelet, proposed in 1909 by Alfred Haar. Due to the facts, this wavelet is not continuous; it offers an advantage for detecting sudden transitions, such as the QRS complex in ECG. The Haar wavelet's mother wavelet function can be described as Eq. 4.

$$\Psi(t) = \begin{cases} 1, 0 \le t < \frac{1}{2} \\ -1, \frac{1}{2} \le t < 1 \\ 0, 0 > t \ge 1 \end{cases} \quad (4)$$

The Daubechies wavelets (Fig. 8), named after her inventor Ingrid Daubechies, are a family of orthogonal wavelets characterized by a maximal number of vanishing moments. This type of wavelet is easy to put into practice using the fast wavelet transform but it is not possible to write down in closed form.

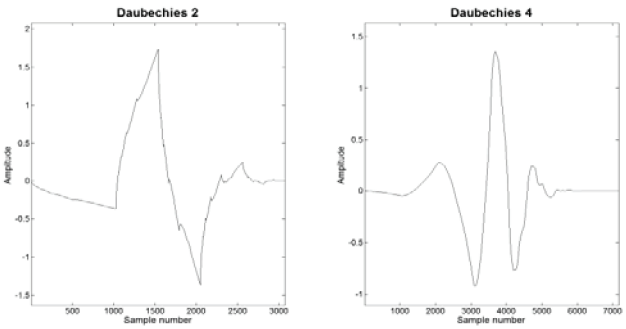

Fig. 8. Daubechies 2 and 4 mother wavelets

Symlets (Fig. 9) are also known as the Daubechies least asymmetric wavelets and their construction is very similar to the Daubechies wavelets. Daubechies proposed modifications of her wavelets that increase their symmetry while retaining great simplicity.

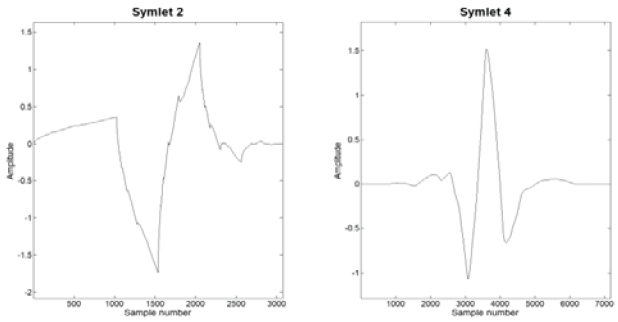

Fig. 9. Symlet 2 and 4 mother wavelets

Coiflets (Fig. 7) are a family of orthogonal wavelets designed by Ingrid Daubechies to have better symmetry than the Daubechies wavelets.

Finally, the pre-processing section concludes reducing the number of variables remaining by the first level of wavelet transform. In the case of the subnet without integral transformation, simply the signal is downsampled.

The DWT of an ECG signal is calculated by passing it through a series of filters related by pairs (quadrature mirror filter), being decomposed simultaneously with a low pass filter (approximation coefficients) and with a high pass filter (details coefficients), and later, downsampled by 2. In this study, the wavelet filter outputs selected as inputs to the next stage (MLP) are the approximation coefficients of the very first level.

As the Nyquist's sampling theorem states: "If a function x(t) contains no frequencies higher than B hertz, it is completely determined by giving its ordinates at a series of points spaced 1/(2B) seconds apart." Thus, as the original ECG is sampled at a frequency of 1.000 Hz and later is filtered by a pass-band between 0.5 Hz and 45 Hz, the information is contained up to 45 Hz and the signal is sampled with a oversampling factor of about 22. This means that the signal can be downsampled by a factor up to 22 without losing significant information. In this study, the downsampling factor selected reduces the number of samples from about 100 to 20 samples (about 5) in the Simple-MLP net.

5. MLP implementation

In this study we have designed two system focused in a different family of ischemia; the first family is composed by anteroposterior ischemia, and the second family is composed by inferolateral ischemia. For each system seven different MLP have been tested, one for each selected ECG signals pre-processing. These ANN are Haar-MLP, D2-MLP, D4-MLP, COIF1-MLP,

SYM2-MLP, SYM4-MLP, and Simple-MLP (with no DWT).

As shown in Fig. 2, the basic MLP used in this study is formed by three layers: the input layer (with as many neurons as inputs has the net, generally about 20 neurons), one hidden layer (it has been estimated empirically the optimal number of neurons for each ANN - Table 1), and the output layer (which consists of a single neuron). In this study, 20 ANN were trained for each number of neurons in hidden layer in order to select the best one (20 nets for 50 different number of neurons in hidden layer).

Table 1. Results of number of neurons in hidden layer experiment

Nº	Sens Max	Sens Mean	Sens Min	Spec MAX	Spec Mean	Spec Min
14	94,23%	89,56%	82,69%	97,18%	94,71%	90,40%
15	91,35%	87,64%	83,65%	96,05%	94,39%	90,96%
16	93,27%	89,70%	86,54%	96,05%	93,99%	90,40%
17	95,19%	89,29%	81,73%	98,31%	94,71%	91,53%
18	94,23%	89,84%	85,58%	98,31%	94,27%	89,27%

Table 1 shows the results obtained in the number of neurons in hidden layer experiment (only 14-neurons to 18-neurons results are shown, but 1-neurons to 50-neurons have been tried). The optimal number of neurons is not associated to the best value of sensitivity or specificity separately, but a compromise between the two factors. So, 18 neurons in the hidden layer were selected for our system.

Therefore, the training algorithm has to calculate the value of the weights which allow the network to correctly classify the ECG. The selected training algorithm was the scaled conjugate gradient back-propagation (23). This method is a supervised learning method, and is a generalization of the delta rule. Since each ECG was previously diagnosed by a team of cardiologists, using a supervised method is a good choice. The scaled conjugate gradient back-propagation algorithm is based on conjugate directions, but this algorithm does not perform a line search at each iteration. Training stops when the performance gradient falls below 1e-5 or the validation performance has increased more than 6 times since the last time it decreased. The initial weights values were set randomly at the beginning of each training. The convergence of the algorithm is achieved by minimizing the root mean square error (known also as the cost function) between the estimated value and the real value. The minimization of the cost function is achieved through the optimization of the weights.

6. Results and discussion

6.1. *Training results*

Training data of ECG ischemia used in this study was taken from the Gem-Med database. Training patterns had been originally sampled at 1.000 Hz before any filtering, so they were arranged as about 950 samples in the intervals of R–R for all diagnostics, which we call as a complete window. Firstly, the segment selection (QRS complex and T wave for this study) produces an initial reduction in the number of samples about 400.

Training patterns were formed in mixed order from the ECG pre-processed. The size of the training patterns is 3 leads of about 20 samples for the first system (anteroposterior ischemia detector) and 2 leads of about 20 samples for the second system (inferolateral ischemia detector), i.e. 3 leads each including about 20 samples, so, 60 samples are present. The combination of these training patterns was called as training set.

The optimum number of hidden nodes and learning rate were experimentally determined for each ANN structure. After the proposed structures were trained by the training set, they were tested for healthy ECG. For the stopping criterion of all the networks, the maximum number of iterations was set to 10 000 and the desired error value (MSE) was set to 0.001. MLP models have been trained with the training data including a predetermined number of leads depending on the pathology targeted, and the architectures that can produce best results have been determined with trial and error. The test was implemented using ECG records taken from about 800 patients.

6.2. *Test results*

The results of classification for the anteroposterior ischemia detector are resumed in Table 2, and those for the inferolateral ischemia detector are resumed in Table 3. Each row of the table represents the instances in a specific ANN.

Table 2. Anteroposterior ischemia MLP results

Subnet	Training set			Test set		
	Sens	Spec	MC	Sens	Spec	MC
No WT	94,23%	91,53%	87,17%	64,15%	82,24%	63,04%
Haar	91,35%	94,92%	85,81%	65,09%	84,62%	55,57%
D2	88,46%	94,35%	78,52%	78,30%	80,98%	62,07%
D4	93,27%	94,92%	85,81%	68,87%	81,12%	63,19%
Coif1	88,46%	96,05%	78,55%	67,92%	86,85%	65,19%
Sym2	87,50%	90,40%	84,34%	66,98%	83,92%	61,21%
Sym4	90,38%	97,74%	78,64%	64,15%	85,87%	66,49%

Table 3. Inferolateral ischemia MLP results

Subnet	Training set			Test set		
	Sens	Spec	MC	Sens	Spec	MC
No WT	89,29%	96,84%	84,45%	72,73%	91,01%	36,55%
Haar	91,07%	94,74%	86,26%	74,33%	85,33%	40,37%
D2	82,14%	94,74%	83,15%	79,14%	87,22%	44,95%
D4	91,07%	94,74%	87,85%	77,54%	88,80%	38,54%
Coif1	83,93%	93,68%	85,42%	80,75%	88,49%	45,73%
Sym2	89,29%	94,74%	77,32%	75,94%	88,33%	40,77%
Sym4	85,71%	92,63%	89,28%	77,54%	90,85%	41,49%

The first group of columns represents the statistical measures of the performance of the ANN with the training set: Sensitivity (Sens), Specificity (Spec) and the Matthews correlation Coefficient (MC). The second group of columns represents the same quality parameters of the ANN with the test set. The statistical measures of the performance of the binary classification test used in this study are the following (23):

Sens column represents sensitivity of the system, related to the system's ability to identify pathological patients. A high value means there are few pathological cases which are not detected by the system. This can also be written as Eq.5.

$$Sens = \frac{TP}{TP + FN} \tag{5}$$

Spec column represents specificity of the system, related to the system's ability to identify healthy ECG. A high value means there are few healthy cases which are marked as pathological by the system. This can also be written as Eq.6.

$$Spec = \frac{TN}{TN + FN} \tag{6}$$

MC column represents the Matthews correlation Coefficient, which is used as a measure of the quality of binary classifications (two-class – pathological and non-pathological ECG). A high value means that both, sensitivity and specificity are high and the system is very reliable. This can also be written as Eq. 7.

$$MC = \frac{(TP * TN - FP * FN)}{\sqrt{(TP + FP) * (TP + FN) * (TN + FP) * (TN + FN)}} \tag{7}$$

7. Conclusion

In this work we have presented two-stage MLP model for ECG signal diagnosis. We focused on two main ischemia diagnosis groups, namely, anteroposterior and inferolateral ischemia. The automatic detector of ischemia consists of two stages, namely, feature extraction and classifier. The first stage has been implemented with a segmentation module, which is responsible for selecting the section of interest of the ECG, and a pre-processing module, which performs the ECG feature extraction itself. For this work, several wavelet transforms have been compared. The second stage is implemented with MLP, because there are several different WT, several MLP had to be trained, one for each.

The best sensitivity for a single net of the first system is DB2-MLP, which has been able to differentiate healthy patients from diagnosis of anteroposterior ischemia with 78.30% of sensitivity and 80.98% of specificity. The best sensitivity for a single net of the second system is Coif1-MLP, which has been able to differentiate healthy patients from diagnosis of inferolateral ischemia with 80.75% of sensitivity and 88.49% of specificity.

These results are very promising and encourage us to extend this study to other heart diseases and to investigate other pre-processing and post-processing stages.

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8. References

1. Klabunde, R.E. Cardiovascular physiology concepts. Philadelphia : Lippincott Williams & Wilkins, 2011. ISBN 9781451113846.

2. Bayès de Luna, Antoni. Bases de la electrocardiografía. De las variantes de la normalidad a los patrones diagnósticos (III): Isquemia, lesión y necrosis. Barcelona : Prous Science, 2007. B-1749-07.
3. Noise and baseline wandering suppression of ECG signals by morphological filter. Taouli, S.A. and Bereksi-Reguig, F. 2010, Journal of medical engineering & technology, Vol. 34, pp. 87-96.
4. Comparative study of morphological and time-frequency ECG descriptros for heartbeat classification. Christov, I., et al. 2006, Medical engineering & physics, Vol. 28, pp. 876-887.
5. ECG signal conditioning by morphological filtering. Sun, Y., Chan, K.L. and Krishnan, S.M. 2002, Computers in biology and medicine, Vol. 32, pp. 465-479.
6. Evolving a Bayesian classifer for ECG-based age classification in medical applications. Wiggins, M., et al. 2008, Applied soft computing, Vol. 8, pp. 599-608.
7. ECG signal denoising using higher order statistics in wavelet subbands. Sharma, L.N., Dandapat, S. and Mahanta, A. 2010, Biomedical signal processing and control, Vol. 5, pp. 214-222.
8. Comparison of logistic regression and Bayesian-based algorithms to estimate posttest probability in patients with suspected coronary artery disease undergoing exercise ECG. Morise, A.P., et al. 1992, Journal of electrocardiology, Vol. 25, pp. 89-99.
9. The comparison of different feed forward neural network architectures for ECG signals diagnosis. Gholam, H., Luo, D. and Reynolds, K.J. 2006, Medical engineering & physics, Vol. 28, pp. 372-378.
10. Evolving neural networks using a genetic algorithm for heartbeat classification. Sekkal, M., Chick, M.A. and Settouti, N. 2011, Journal of medical engineering & technology, Vol. 35, pp. 215-223.
11. A qualitative comparison of ANN and SVM in ECG arrhythmias classification. Moavenian, M. and Khorrami, H. 2010, Expert systems with applications, Vol. 37, pp. 3088-3093.
12. ECG signal compression using combined modified discrete cosine and discrete wavelet transforms. Ahmed, S.M., et al. 2009, Journal of medical engineering & technology, Vol. 33, pp. 1-8.
13. Generation of digital time database from paper ECG records and Fourier transform-based analysis for disease identification. Mitra, S., Mitra, M. and Chaudhuri, B.B. 2004, Computers in biology and medicine, Vol. 34, pp. 551-560.
14. A comparative study of DWT, CWT, and DCT transformations in ECG arrhythmias classification. Khorrami, H. and Moavenian, M. 2010, Expert systems with applications, Vol. 37, pp. 5151-5157.
15. ECG analysis using wavelet transform: application to myocardial ischemia detection. Ranjith, P., Baby, P.C. and Joseph, P. 2003, ITBM RBM, Vol. 24, pp. 44-47.
16. Comparison of FCM, PCA and WT techniques for classification ECG arrhythmias using artifical neural network. Ceylan, R. and Ozbay, Y. 2007, Expert systems with applications, Vol. 2007, pp. 286-295.
17. A patient adaptable ECG beat classifier based on neural networks. Gaetano, A., et al. 2009, Applied mathematics and computation, Vol. 213, pp. 243-249.
18. A new method for classification fo ECG arrhythmias using neural network with adaptative activation function. Ozbay, Y. and Tezel, G. 2010, Digital signal processing, Vol. 20, pp. 1040-1049.
19. ECG beat classification using swarm optimization and radial basis function neural network. Korurek, M. and Dogan, B. 2010, Expert systems with applications, Vol. 37, pp. 7563-7569.
20. Daubechies, Ingrid. Ten lectures on Wavelets. Philadelphia : Society for Industrial and Applied Mathematics, 1992. ISBN 0-89871-274-2.
21. Wavelets and filter banks: theory and design. Vetterli, M. and Cormac, H. 1992, IEEE Transactions on signal processing, Vol. 40, pp. 2207-2232.
22. Detection of ECG characteristic points using wavelet transform. Li, C., Zheng, C. and Tai, C. 1995, IEEE Transactions on biomedical engineering, Vol. 42, pp. 21-28.
23. Assessing the accuracy of prediction algorithms for classification: an overview. Baldi, P., et al. s.l. : Bioinformatics review, 2000, Vol. 16, pp. 412-424.