APPLICATION OF NEURAL NETS TO DETECT ARTRIAL PREMATURE BEAT (APB)

M.A.Chikh, N.Belgacem, Az. Chikh, F.Bereksi-Reguig.
Laboratoire de Génie Biomédical, Département d'Electronique, Faculté des Sciences de l'Ingénieur, Université Abou Bekr Belkaïd, Tlemcen B.P 230 pole Chetouane, 13000 Algérie.
Email mea_chikh@mail.univ-tlemcen.dz
Fax : 243 43 28 56 85

Abstract- The atrial activity of the human heart is normally visible in the electrocardiogram (ECG) signal as a P-wave. In patients with intermittent artery heart disease, a different P-wave morphology can sometimes be seen, indicating atrial conduction defects. The purpose of this study was to use a supervised neural network (NN)-based algorithm to discriminate between an atrial premature beats (APB) and normal ones. The performance of the method was measured using eight recordings of each type from MIT-BIH database, based on the morphology of the P-wave and the duration of the QS segment between the Q-wave of the APB beat and the previous S-wave. The method achieved a sensitivity of 92 % and a specificity of 89 % in discrimination of APB beats from normal ones. The results show that neural networks can be used in electrocardiogram (ECG) processing in cases where fast and reliable detection of artrial premature beat is desired as in the case of critical units (CCU's).

Index Terms- Neural network, MIT-BIH arrhythmia database, Atrial Premature Beat, P-wave.

1. Introduction

The heart, in its simplest form, may be considered as a pump for the circulation system. Its function is to rhythmically contract, pumping blood to the lungs for oxygenation, and then pumping the oxygenated blood into the general circulation. The heart consists of four chambers, two atria and two ventricles. The ventricles are considered to be ejecting chambers, and the atria receiving chambers. The atria, during ventricular ejection may merely be considered to be blood stores. Electrical currents, which spread through the heart, initiate the signal for cardiac contraction. The origin of the stimulus, under normal conditions is the Sinoatrial node, located in the right atrium. Chambers are forced to contract as the signal spreads through the heart, pumping blood throughout the body. The recorded sequence of the electrical stimulus in the heart is referred to as the electrocardiogram or more commonly as the ECG. Each component of the ECG is directly related to the spread of electrical stimulus through a specific part of the heart. Fig. 1 indicates the relationship between the spread of stimulus and the characteristic shape of the ECG.

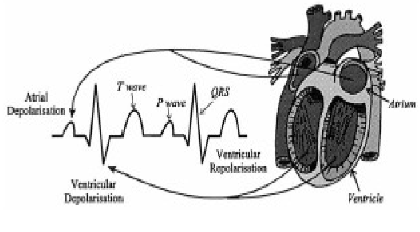

Fig1. Spread of electrical stimulus throughout the heart.

The P wave represents atrial depolarization (cardiac stimulation), the QRS complex represents ventricular depolarization, and the T wave represents the return of the ventricles to their resting state (repolarization). There is no visible waveform for atrial repolarization as it is engulfed by ventricular depolarization. When the conduction within an atrium or between the two atria is different from the normal situation, the morphology of the P-wave changes. The impulse is discharged prematurely by some irritable focus in the atria giving rise to a distorted P-wave (wide, narrow, notched, inverted or superimposed on the preceding T-wave). The further from the SA node the ectopic focus is, the more abnormal will be P' configuration. PR interval normal or slightly prolonged. Premature P followed by QRS less than 0.11 sec except when very premature P is not conducted. The pause between APB and the next sinus beat is usually noncompensatory, i.e., the RR interval between two QRS enclosing APB is less than twice the normal RR interval (Fig. 2).

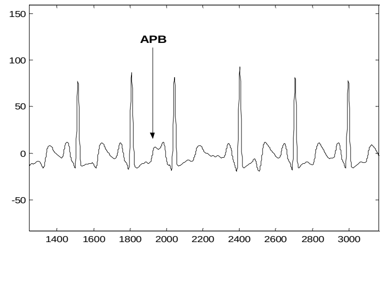

Fig2. Position of the APB beat in the ECG signal.

Modern approaches to ECG interpretation by computer are basically of two types. One is called the deterministic approach, where various diagnostic criteria are programmed into a computer. On the other hand, the second approach, namely, the statistical technique, assesses the likelihood of a collection of measurements belonging to one of several mutually exclusive diagnostic categories.

Neural networks (NNs) have been widely used over the past few years as pattern and statistical classifiers [1],[2] in many application areas including medicine [3]. For example, NNs were used for QRS/PVC classification [4], [5], or for detection of atrial fibrillation [6]. Neural networks-based P-wave analysis has been used for automated detection of the atrial premature beat, with a backpropagation (BP) NN using inputs of measured parameters such as P-wave morphology, and duration of the SQ segment between the Q-wave of the APB beat and the previous S-wave. The paper is organized as follows. Section II describes the methods used for the preprocessing of the ECG segments. Description and training of the NN is discussed in section III. Experimental results are presented in section IV. Finally, conclusions are drawn in section V.

2. ECG Preprocessing

The main objective of the preprocessing is to reduce interference due to noise and extract a minimal set of parameters which adequately represents each P-wave without sacrificing classification performance of the ANN classifier.

A. Holter Recording Selections

Selected data was taken from the MIT/BIH arrhythmia database [7] for normal and APB beats and used to detect and classify these 44conditions using the neural network method. Height patient ECG's were selected from the database shown in Table 1. The sampling frequency of the ECG signals in the database is fs=360 Hz. This database is intended to be used for the evaluation of algorithms for pathologies analysis based on QRS and P wave changes. Working independently, the two expert cardiologist-annotators visually checked the full disclosure printouts and manually inserted annotations indicating changes in QRS and P morphology, rhythm, and quality. Annotations from the two cardiologists were compared and the differences were resolved by a third cardiologist.

B. Bandpass Filtering

With the advent of low-cost microcomputers and data-acquisition systems, digital filters are fast replacing their analogue counterparts. The electrocardiogram (ECG) obtained from body electrodes has the following unwanted noise components:

a- Baseline wander; which may be caused due to a number of factors arising from biological or instrument sources such as electrode skin resistance, respiration and amplifier thermal drift.

b- 60 Hz power-line interference

c- 100 Hz interference from fluorescence lights. Several integer coefficient recursive FIR filters have been reported in the past [8],[9],[10],[11]. The proposed integer coefficient band-pass filter achieves the elimination of both 60 and 100 Hz interferences along with the low-frequency baseline wander [12].

Its transfer function is given by

$$\mathbf{H(Z) = (1\text{-}z^{-360})(1+z^{-150})/(1\text{-}z^{-6})}$$

TABLE 1
EVALUATION DATA TAKEN FROM MIT BIH ARRHYTHMIA DATABASE

records	Normal Beats	APB Beats
# 100	2239	33
# 200	1820	10
# 202	1743	30
# 207	2061	36
# 209	0	107
# 213	2621	382
# 222	2062	208
# 223	2029	72

3. Description and Training of the NN

For the purpose of training the network, twenty time-normalized amplitudes in the P wave were used. In addition, the duration of SQ interval was input [13].

Before the data could be input to the network for training, it was necessary to normalise or scale them. With the sigmoid activation function, the output of a neuron lies in the range 0-1. ideally, therefore, input data should be normalised such that they lie in this range. The formula used for normalising the data was as follows :

$$X_{new} = \frac{X_{old} - X_{\min}}{X_{\max} - X_{\min}}$$

this pr4ocess was applied to each of the input variables, where X_{max} and X_{min} were the maximum and the minimum values for the particular parameter being used. Note that these values could be positive or negative.

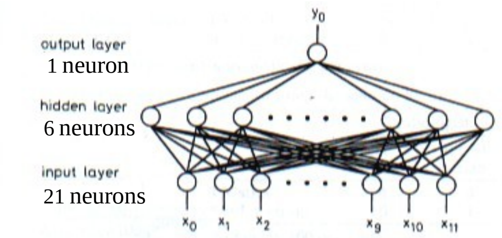

Fig. 3 *Topology of the neural network used for this study*

The number of neurons (N_h)in the hidden layer was chosen to be six, the value of N_h was determined heuristically, so as to decrease the training time of the NN.

For the third layer (output layer), one neuron was used. The output of each of these neurons assumes a value between zero and one, wich is rounded to one if higher than 0.5 or to zero otherwize. The resulting two output combinations serve to identify two beat classes: normal beats or APB beats.

A BP algorithm was used for the training procedure. This BP algorithm changes the weughts of NN so as to minimize the error or energy function E, defined by the equation :

$$E = \sum_{k=1}^{M} \left\| \vec{o}_K - \vec{t}_k \right\|^2$$

where M is the size of the training set, $\vec{O}_k$ the output vector of NN, and $\vec{t}_k$ the target vector for each training pair k. Each unit of the network uses the sigmoid activation function $f(x) = 1/(1+e^{-\alpha+\beta})$, where α and β are constants that determine the transition of the neural unit.

The procedure for the training of the NN is based on an adaptive algorithm with the parameter α changing, so as to help avoid entrapment into local minima. Specifically, our purpose is to minimization of the energy function E

$$\Delta w = \alpha \frac{\partial E}{\partial w}$$

where in this equation w is the weight vector of the weights between the input and the hidden layer. If in the above equation $\partial E / \partial w = 0$, a minimum has been reached. To test whether this is a local minimum, the value of α is increased by 10% and trainig resumes. When E starts decreasing again, the value of α is restored to 90% of its original value. This heuristic method does not guarantee convergence to the global minimum. In our case, however, it works well and dramatically decreases the training time.

The performance of the algorithm was evaluated by computing the percentages of sensitivity(SE), specificity (SP) and correct classification (CC), the respective definitions are as follows:

Sensitivity: [SE = 100xTP/(TP+FN)] is the fraction of real events that are correctly detected among all real events.

Specificity: [SP = 100xTN/(TN+FP)] is the fraction of nonevents that has been correctly rejected.

Correct classification:
[CC=100x(TP+TN)/(TN+TP+FN+FP)] is the classification rate.

Where TP was the number of true positives, TN was the number of true negatives, FN was the number of false negatives, and FP was the number of false positives. Since we are interested in estimating the performance of classifiers based on the recognition of PVC beats, the true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN) are defined appropriately as shown below:

FP: classifies normal as PVC.
TP: classifies PVC as PVC.
FN: classifies PVC as normal.
TN: classifies normal as normal .

4. Experimental results

The results of the evaluation of the algorithm in terms of correct classification sensitivity and specificity are summarized in table 2 (actual number of beats) and table 3 (percentage).

TABLE 2

BEAT–BY-BEAT RECORD-BY-RECORD TESTING RESULT OF THE EXPERIMENT

Records	**TP**	**FP**	**FN**	**TN**
# 100	32	3	0	93
# 200	27	11	2	76
# 202	35	0	0	105
# 207	104	0	1	0
# 209	355	182	26	961
# 213	24	20	0	52
# 222	189	0	18	621
# 223	70	12	1	201

TABLE 3
PERFORMANCE OF THE ALGORITHM. ALL ENTRIES ARE IN PERCENT (%) .

Records	Specificity	Sensitivity	Correct Classification	Predictivity
# 100	96.87	100	97.65	91.42
# 200	87.35	93.10	88.79	71.05
# 202	100	100	100	100
# 207	NaN	99.04	99.04	100
# 209	84.07	93.17	86.35	66.10
# 213	72.22	100	79.16	54.54
# 222	100	91.30	97.82	100
# 223	94.36	98.59	95.42	85.36

These results show a good performance for normal and abnormal APB beats identification using neural networks. The average results obtained by the algorithm were:
93.03 correct classification, 90.69 specificity and 96.90 sensitivity.

5. Conclusions and further work

We have presented a novel method that employs ANN's for the automated detection of atrial premature beat (APB) in long duration ECG recordings. In order to train the network a MIT-BIH database was used containing beats that are annotated as APB, normal or others.
The performance of the system was better than other reported when tested with MIT-BIH database.
A disadvantage of the proposed method is that it cannot provide any interpretation, for the decisions made due to the employment of the neural network model. Proper combination [14] of the knowledge-based approach [15] with the neural network model can eliminate this drawback. The potential of our method will be further assessed in recordings from ambulatory patients and patients undergoing continuous ECG monitoring in the coronary care unit.

References

[1] D.R. Hush and B.G.Horne, "Progress in supervised neural networks-what's new since Lippmann ?", *IEEE signal proc.Mag, pp 1-39,1993.*

[2] J.A.Freeman and D.M.Skapura, "Neural networks : Algorithms, applications and programming techniques reading", *MA:Addison Wesley, 1991.*

[3] A.S. Miller, B.HBlott and T.K.Hames, "review of neural network applications in medical imaging and signal processing", *Med, boil.Eng, Comput, vol 30, pp 446-464,1992.*

[4] M.Strintzis, X.Magnisalis,G.Stalidis, and N.Maglaveras, "Use of neural networks for elelctrocardiogram (ECG) feature extraction recognition and classification", *neural network world J, vols 3-4,pp.313-327,1992.*

[5] H.Chow, G.B.Moody, and R.G.Mark, "Detection of ventricular ectopic beats using neural networks", *in computers in cardiology. Los Alamitos, CA: IEEE, comput. Soc. Press, pp.659-662, 1992.*

[6] S.G.Artis,R.G.Mark and G.B.Moody, "Detection of atrial fibrillation using artificial neural networks", *in computers in cardiology. Los Alamitos, CA : IEEE Comput. Soc. Press, pp.173-176, 1991.*

[7] "MIT/BIH arrhythmia database directory", *(CD-ROM), Harvard Univ. and Mass Inst. Of tech. Div of health sciences and tech, Cambridge, MA, document BMEC, july 1992.*

[8] P.A.Lynn, "recursive digital filters for biological signals" *Med. & Biol. Eng. 9, 37-44, 1971.*

[9] P.A.Lynn, "Online digital filters for biological signals: some fast design for a small computer", *Med. & Biol. Eng. & Comput. 15, 534-540, 1977.*

[10] P.A.Lynn, 'Tranversal resonator digital filters : fast and flexible online processors for biological signals", *Ibid,21,718-730, 1983.*

[11] N.V. Thakor, and D.Moreau, "Design and analysis of quantized coefficient digital filters : application to biomedical signal processing with microprocessors", *Med & Biol. Eng. & Comput. 25, 18-25, 1987.*

[12]R.Wariar and D.Moreau, "Integer coefficient bandpass filter for the simultaneous removal of baseline wander, 50 and 100 Hz interference from the ECG", *Med & Biol. Eng. & comput., 29,333-336, 1991.*

[13] P.Laguna, N.V.Thakor,P.Caminal, "New algorithm for QT interval analysis in 24 hour Holter ECG : performance and applications", *Med &Biol. Eng. & Comput., 28,67-73, 1990.*

[14]D.Nanck,F.Klawonm,R.kruse, "Fondations of neuro-fuzzy systems", *chichester:wiley, 1997.*

[15] C. Papaloukas, D.Fotiadis, "A knowledge-based technique for automated detection of ischemic episodes in long duration electrocardiograms", *Med & boil Eng. & Comput.,39,105-112, 2001.*