Two Neural Networks Architectures for Detecting AVB

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Abstract: - The purpose of the paper is to present two networks. These networks were fed with same measurements from one lead of the electrocardiogram (ECG) but in different architectures. The first one based on a compound neural network (CNN) composed of three different multilayer neural networks of the feed forward type, and the second one based on only a multi-layer perceptron (MLP). Such both of them have the capability to classify ECGs as carrying atrioventricular blocks (AVB) or not. For each test case in the test set the neural networks classifier present an output value between 0 and 1. A threshold in this interval was used above which all values were regarded as consistent with AVB. The difference in performance between the two neural networks classifiers was measured as the difference in area under the receiver operating characteristic (ROC) curves.

Key-Words: - Artificial neural networks, Electrocardiogram (ECG), Medical diagnosis, multilayer perceptron (MLP), Pattern recognition, Signal processing.

1 Introduction

Body In healthcare many problems regarding decision making are often difficult and involve complex pattern recognition tasks. This requires expertise, usually in terms of more experienced colleagues, but it could also be in terms of computer-based decision support systems [1]. Artificial neural networks (ANN) are a technology that has turned out to be useful for many biomedical problems occurring in healthcare [2]. In the two last decades, there were close on 1000 citations of neural networks in the biomedical literature [3], mostly describing studies with historical data. Most of these papers used current neural network methodologies, almost invariably the multi-layer perceptron (MLP). Among the first ones, in diagnosis an acute myocardial infarction, were Baxt et al. [4, 5] that used patient history together with ECG data and clinical findings as inputs to the ANNs. A drawback with the ANN of these studies is that some of the input data may be unavailable at the time of initial patient presentation. Heden et al. [6] were able to detect AMI with a performance better than an experienced cardiologist (10.5% sensitivity increase at a specificity level of 86.3%). In another study [7] the others have used Bayesian ANNs as a tool for detecting AMI patients using the 12-lead ECG. The key ingredients of their approach are: a representation of the ECG using Hermite functions, and a combinatorial optimization problem formulation for finding important ANN inputs. Other different applications are to describe a key classification model and visualization platform based on self-adaptive neural networks [8], and a classification between patients and normal subjects was focus on two diseases: Obstructive Sleep Apnea (OSA) and Congestive Heart Failure (CHF) [9].

The present research work aims at developing two approaches. The first one based on a compound neural network (CNN) composed of three different multilayer neural networks of the feed forward type, and the second one based on only a multi-layer perceptron (MLP). Such both of them have the capability to classify ECGs as carrying atrioventricular blocks (AVB) or not. An AVB occurs when atrial conduction to the ventricle is for some reason blocked at a time when the AV junction is not yet physiologically
refractory. In such cases, the ECG will quite often provide adequate information to make a diagnosis regarding the presence of an AVB. As a matter of fact an AVB manifests itself, through the ECG plots, by a slowdown of the heart rate and a relative prolongation of the P-R interval to more than 0.20 s. We can also notice either a progressive prolongation of the P-R interval prior to a non conducted P wave or a constant R-R and P-R intervals prior to a non conducted P wave.

2 The method

Our work has been organized into three parts. The first part is the population study. The second one is related to the preparation of digitized signal for input to the two neural networks, CNN and MLP. The latter part must be realized carefully for it influences considerably the final result by minimizing the noise contained in the digitized signal and providing suitable input vectors for Neural Networks. The third part concerns the training and recall procedures used by the Two networks whose were trained to classify ECGs AVB or no AVB (i.e. or normal) these networks were fed with same measurements from lead II but in different architectures. Finally, performance assessment of the two approaches in detecting AVB was presented in receiver operating characteristic (ROC) curves. A general structure of the algorithm diagram is shown in Fig.1.

2.1 Population study

The study was based on one lead data recorded from patients who had undergone diagnostic at the hospital during the last four years. Patients are adults, both female and male, with known heart problems and symptomatic descriptions. The patients were discharged with the diagnosis AVB. Healthy subjects were randomly selected from a defined urban population. The subjects were examined and interviewed. They had no known or suspected heart disease, or any pathological condition which may influence the ECG. ECGs with severe technical deficiencies and pacemakers ECGs were excluded. Several patients contributed with more than one ECG; i.e., one patient presenting to the cardiology department on two or three different occasions contributed with two or three ECGs. Each discharge diagnosis was confirmed by a cardiologist at the cardiology department.

The AVB group consists of 108 ECGs recorded on men and 90 ECGs recorded on women. The normal group consisted of 73 ECGs recorded on men and 60 ECGs recorded on women. So, there were a total of 331 ECGs.

2.2 Recording technique

All recordings were made digitally. We noticed that the frequency range of the Samples was in accordance with the American Heart Association (AHA) specifications. And the measurements follow the recommendations of the CSE working party. Measurements durations and amplitudes of the waves and the intervals were performed using...
custom software. In first, a filter will be used to eliminate artefacts and to adjust the baseline in order to recognize patterns in the ECG leads.

The system uses the neural network nodes for waveform classification. While other algorithms were considered, we decided that using a neural network would give us the best general functionality with other algorithms used secondarily for specific other characteristics. The following automated measurements from the lead II were considered in the present study: the QRS amplitudes and durations, the P amplitudes and durations, the RR intervals between two successive R waves, PP intervals between two successive P waves and PR intervals between P wave and QRS complex). These parameters were chosen because they are the conventional criteria in detecting AVB in an ECG and were applied as inputs to the CNN and MLP. These measurements were obtained from the computerized ECG recorders using their measurements program.

2.3 Multi-layer perceptron (MLP) architecture
A feed forward type multilayer neural network was experimented. The network itself includes three layers as depicted in Figure.2.

The thirty five parameters are injected into the input layer. These parameters are: Five QRS amplitudes, five QRS durations, five P amplitudes, five P durations, five PR intervals, five RR intervals and five PP intervals durations. Such a configuration calls for an input layer of at least 35 neurons.

The hidden layer has ten neurons. The empirically chosen number of 10 neurons was found to avoid repetition problems and allows minimizing the training time. Each of the neurons in the hidden layer was connected to all of the neurons in the input layer and to the neuron in the output layer. Each connection was characterized by separate weight. The weights were used in the calculations producing numerical output as results of electrocardiographic measurements fed to the network. In a learning process the weights were automatically adjusted using the levenberg- Markwed algorithm in order to give the desired output of each of the ECGs in the learning set. After the learning process was completed, the weights were fixed and all ECGs in the test set were processed once by the network. The terminating single output unit encodes the probability of AVB occurrences.

2.4 Compound Neural Network (CNN) architecture
Three different feed forward type multilayer neural networks were experimented. Two of these networks, (NN1) and (NN2), were set in a parallel configuration in series with the third one (NN3). Fig. 3 shows such a structure.

The network NN1 itself includes three layers. Twenty parameters are injected into the input layer. These parameters are: Five QRS amplitudes, five QRS durations, five P amplitudes and five P durations. The hidden layer includes three neurons while the last layer calls for a single neuron used as an input to NN3 which forms a two-layer network whose input layer is a recipient for NN1 and NN2 outputs. A terminating single output unit encodes the probability of AVB occurrences.
Once the number of layers, and units in each layer, has been selected, the network’s weights and thresholds must be set so as to minimize the prediction error made by the network. This is the role of the training algorithms.

\[ W_{k+1} = W_k - [J^T J + \eta I]^{-1} J^T E \]

\( J \): the Jacobian matrix is much less complex than computing the Hessian matrix.

\( W_{k+1} \): value of the weight at step (k+1) after adjustment and \( W_k \): value of the weight at step (k) before adjustment.

The full Jacobian was not had to exist at one time. We computed the approximate Hessian by summing a series of subterms like update:

\[ H = J^T J = \left[ \begin{array}{cc} J_1^T J_1 & \cdots \\ J_m^T J_1 & \cdots \\ \vdots & \ddots & \ddots \\ J_m^T J_m & \cdots \\ \end{array} \right] \]

For training CNN only half of it was computed at one time. Once one subterm has been computed, the corresponding submatrix of the Jacobian was cleared. This saves half the memory used by the calculation of the full Jacobian. So memory was sufficient for storage and training. However, in MLP training the jacobian matrix \( J \) was not had to be computed and stored as a whole, it was a large training set and was running out of memory, so it should be better set to 4. The Jacobian was divided into four equal submatrices.

The results show that this technique reduces the computational time and the output errors. Training was terminated at a training error of \( 10^{-25} \) and \( 10^{-15} \) for CNN and MLP respectively. Each network had one output neuron. The output of the networks was a number between 0 and 1. The desired output of a network classifying ECGs as AVB or no AVB was 1 for AVB and 0 for no AVB.

### 4 Performance assessments of the CNN and MLP

The performance of the neural networks classifiers was assessed using the test set comprising 215 randomly selected patients from the total population of 331 cases. This test set was not part in any algorithm design or model selection. For each test case in the test set the neural networks classifier present an output value between 0 and 1. A threshold in this interval was used above which all values were regarded as consistent with AVB. The sensitivity and specificity for different thresholds were studied in order to obtain a complete receiver-operating characteristic curve (ROC) for the networks. The results subsequently presented the performances of the networks in the set.

The difference in performance between the two neural networks classifiers was measured as the
difference in area under the ROC curves. The statistical significance of such an observed area difference was assessed by means of a permutation test as follows:

A new classification list was created by randomly selecting for each of the 215 test cases either the classification made with the CNN or the classification made with the MLP. A second list was created from the classification not included in the first one. The two lists were used to construct two ROC curves, and the areas under the curves were calculated, as was the area difference (test statistic). The procedure was repeated many times. The relative frequency of area differences that had an absolute value greater than the actual difference was taken as the probability of obtaining at least the actual area difference if no true difference existed.

5 Results and discussion

The objective of the present study was to compare the performance of two different neural networks; the CNN and MLP architectures. The CNN algorithm was found to be very fast in both test and recall states due mainly to its architecture and the fact that it calls for only one ECG lead which greatly reduces the amount of data required for processing.

The overall speed of the algorithm was very good. The generation of weights was approximately few minutes, but the verification sequence was very quick. The AVB detection looks approximately 2 seconds. The MLP was not as fast as CNN, the training time was more than 10 minutes and the test time was approximately 10 seconds.

The CNN shows a higher sensitivity for all specificities in the range 90% to 100%. However, the difference in sensitivity between the two networks, at a specificity of 99%, was 42% of MLP and 47% vs. 79% of CNN and this difference was highly significant. The significance of the difference in sensitivity between the CNN and MLP was tested with intention to the fact that the same ECGs were used.

Together with the corresponding output values of the CNN. A threshold of 0.1 was used to give sensitivity and specificity 92.31% and 98.39%, respectively. For the MLP the sensitivity was 83% and the specificity was 93.38%. The ECGs with output values close to 1 lack clear electrocardiographic signs of AVB and those with output values close to 0 are clear normal.

In the classification of the ECGs by the CNN and the MLP, there was agreement in 191 ECGs the 6 ECGs on which the CNN and MLP disagreed, and on which the network was incorrect constitute a particularly interesting group one of the six ECGs had serious errors in the data of the measurement program and was therefore not properly presented to the networks.

All the ECGs from the group of the 3 cases falsely classified by the CNN have QRS complexes with abnormal notches. One of them has decreasing R wave amplitude; the others have large QRS complexes.

The decreased R wave progression was not a common finding the material. Therefore, this pattern might be difficult for the network.

The ECGs which have large QRS complexes; this is not a normal finding and the CNN classification is therefore not surprising. This information is not given to the network; the training used only normal QRS. To resolve this problem, it could be to add an expert to the CNN.

4 Conclusion

We have presented two methods for automated detection of AVB patients using one lead ECG. The lead was digitalized and the measurements were used as inputs to the CNN and MLP classifiers that were trained to detect AVB and the same ECGs were used in the test. The performance was compared with that of an experienced cardiologist to whom we presented all the ECGs in random manner. The cardiologist classified each of the ECGs; the
results were available at the classification procedure from the CNN. No significant difference was found. The sensitivity and specificity were 92.30% and 98.39% respectively. For the MLP the sensitivity was 83% and the specificity was 93.38%.

The compared previous results show that the CNN and MLP, both of them can be trained to detect AVBs from the ECG with a performance in terms of accuracy and sensitivity equivalent to what a cardiologist would achieve.

With proper further developments, we believe the proposed CNN has potential as a decision support system that can provide a good suggestion for diagnosis.

The CNN used in the present work can be incorporated in computer-based ECG interpretation system in order to detect AVB in ECG waveforms. Such implementations would yield higher performance particularly in cardiology departments. These good results confirm that neural networks can be reliably used to improve automated ECG interpretation process for AVB and that even an experienced cardiologist could use such networks as an essential decision-making support. This improvement will lead, in the near future, to a more accurate early diagnosis of AVB.

References: