Neural Networks and Fuzzy Logic Approximation and Prediction for HRV Analysis

A. Alexandridi*, C.D. Stylios and G. Manis
University of Ioannina, Dept. of Computer Science
P.O. Box 1186, Ioannina 45110, Greece
Phone: +30-2651098806, Fax: +30-2651098890
email:{manis, stylios}@cs.uoi.gr
*National Technical University of Athens
Zografou Campus, Zografou 15773, Greece
Phone: +30-772-2495, Fax: +30-772-1533
email: aneta@cslab.ntua.gr

ABSTRACT: The heart rate signal contains valuable information and its analysis has proven very useful in distinguishing healthy subject cardiograms from those of subjects with a variety of cardiac pathologies. The approach proposed here introduces a new use of neural network and fuzzy logic concepts for the prediction and approximation of cardiograms in order to differentiate between healthy and unhealthy subjects. Neural networks and fuzzy logic - and even their hybrids - have been applied in previous studies for the analysis of cardiogram data and their predictive/approximation capabilities are exploited in this study for cardiogram categorization. We show that measuring the prediction and approximation error of all methods, as they are applied to each cardiogram, results in a clear distinction between the two groups. This is in coherence with cardiac physiology, since the behaviour of a healthy subject ECG is more erratic than an unhealthy subject's.

KEYWORDS: HRV analysis, neural networks, fuzzy logic, approximation, prediction

INTRODUCTION

The dominant peaks of the ECG signal, the R-peaks, are used as the marker for determining the heart rate, the variability of which has been established as an indication of cardiac health. The physiological explanation behind this rests on the fact that a healthy heart is more adaptive to changes, thus exhibiting a more erratic behaviour compared to an unhealthy heart. Therefore, the heart rate signal of an unhealthy subject is actually more steady and presents a lower variability than that of a healthy subject [1],[2]. This phenomenon has been analyzed and exploited in many studies, including those which are focused on clinical diagnosis.

The simplest HRV analysis methods are those that investigate heart rate properties in the time domain by examining the R-peaks extracted directly from the ECG signal. These include the mean R-R interval, the mean heart rate, the difference between the longest and the shortest R-R interval and other similar measures [3]. Although much work has been done and the bibliography is quite extensive, as of yet there is no single method that is widely accepted to classify and model cardiograms, demonstrating that the heart is indeed a very difficult system to harness. The innovative approach proposed in this paper offers another perspective at cardiogram categorization and actually relies on the fact that the heart rate of healthy subjects is unpredictable and that of unhealthy subjects is not. Therefore, in contrast to other methods [4],[5],[6],[7], we are not attempting to mathematically describe or model cardiac behaviour, but rather we are predicting and/or approximating the signal, taking into consideration precisely the fact that doing to accurately is difficult and unlikely and that the results will produce significant error. Proposed are two methods which attempt to categorize known cardiograms of healthy and unhealthy subjects into two distinct groups. In the one case, a neural network is trained to predict a set of both subject groups. Once the network is trained, the test cardiograms are then passed through it and a first prediction of each is made. The predicted cardiograms are then compared to the originals and the resulting error is computed. Due to the fact that healthy subject cardiograms are more erratic, their prediction error is greater than that of unhealthy subjects. The same principle is investigated with fuzzy logic approximation. Once again, the cardiograms are approximated using fuzzy logic concepts and the resulting data is compared to the original. The error is computed and it is shown that it is greater in unhealthy subject cardiograms. Therefore, we are in essence, measuring the prediction and approximation error, concluding that the larger the error, the more difficult the signal is to predict, and therefore the healthier the subject.

BACKGROUND

Decreased heart rate variability is often related to poor cardiovascular health and has also been associated with a variety of psychological disorders [8],[9],[10],[11],[12]. In order to determine the heart rate of a signal, the QRS complexes are identified and the R-peaks are extracted. The signal of the distances between these peaks is the heart rate and it analysis has been used for many cardiac studies both in the medical and the engineering communities. HRV has been investigated with neural networks and fuzzy logic, and even the combination of the two.

Fuzzy cluster analysis has been used in the classification of stress tests as mildly, moderately or severely abnormal [13] Sets were created for each of six stress test variables and the degree of membership was a measure of the strength of association of these stress variables with their fuzzy sets. This method of analysis showed good overall correlation with the severity of coronary artery disease, and was a better predictor of the extent of Coronary Artery Disease than other methods applied. Fuzzy logic has also been combined with Neural Networks in some studies in an attempt to use HRV as a predictive measure [14],[15]. In [14] a fuzzy neural network, FuNN, was used in order to build an adaptive, intelligent information system that was used for the characterization and prediction of heart rhythms of patients with cardiovascular disorders. The classification performance achieved during training was perfect, with a confidence level very close to 100%. When the trained FuNN was tested with new data sets (not those included in the training sessions), the classification performance was very good.

In this paper, we applied neural networks and fuzzy logic to HRV analysis in a different way than all similar studies. Radial basis function networks were used both for neural prediction and approximation of the cardiograms. The Adaptive Neuro-Fuzzy Inference System (ANFIS) was applied for fuzzy approximation.

RADIAL BASIS FUNCTION NETWORKS

A common method used to model the multilayer perceptron used for time series prediction is the neural network employing radial basis functions (RBFs). An RBF is a multidimensional function which depends on the distance $r = \|x - c\|$ between the input vector x and the center c. Our approach involves the approximation of a nonlinear function with a linear combination of the fixed nonlinear basis functions, illustrated in (1).

$$F(x) = \sum_{i=1}^{h} w_i f_i(x) \tag{1}$$

Radial Basis Functions networks provide a powerful method for multidimensional approximation or fitting. They also do not normally suffer from proliferation of adjustable parameters as the dimensionality of the problem increases. In our approach the radial basis function that was implemented was the Gaussian function, shown in (2).

$$f(r) = \exp\left(\frac{-r^2}{\sigma^2}\right) \tag{2}$$

ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

The ANFIS was first introduced by Jang [16]. It is a fuzzy inference system implemented in the framework of adaptive networks. ANFIS can achieve a highly nonlinear mapping and it is superior to common linear methods in reproducing nonlinear time series. It is best suited for training of Sugeno-type fuzzy systems where the output of each rule is a linear combination of input variables plus a constant term and the final output is the weighted average of each rule’s output. The parameters of a Sugeno FIS can be optimized automatically using a recursive algorithm. The parameters are adapted to learn a specific input-output mapping. The learning scheme is a hybrid one involving both a back-propagation learning rule and a least square scheme. The resulting fuzzy inference system has unlimited approximation power to match any nonlinear functions arbitrarily well on a compact set.

RESULTS

The selection of the subjects was done by a cardiologist according to their medical record. The healthy subject data set is made up of continuous ECG recordings derived from normal young males aged 25-29 yrs, with a clean medical history and normal physical examination. Continuous ECG recordings were also acquired from a group of hospitalised cardiac patients, under similar conditions. To ensure that valid and precise data was acquired, a cardiologist was present to guarantee that all preparation and procedure details during cardiogram acquisition were followed properly.

NEURAL NETWORK PREDICTION

The prediction results of the application of the radial basis function networks to our healthy and unhealthy subject data are depicted in Figure 1.

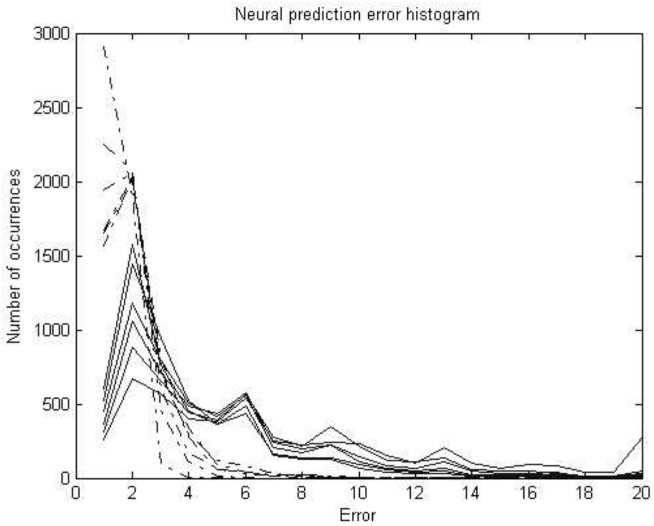
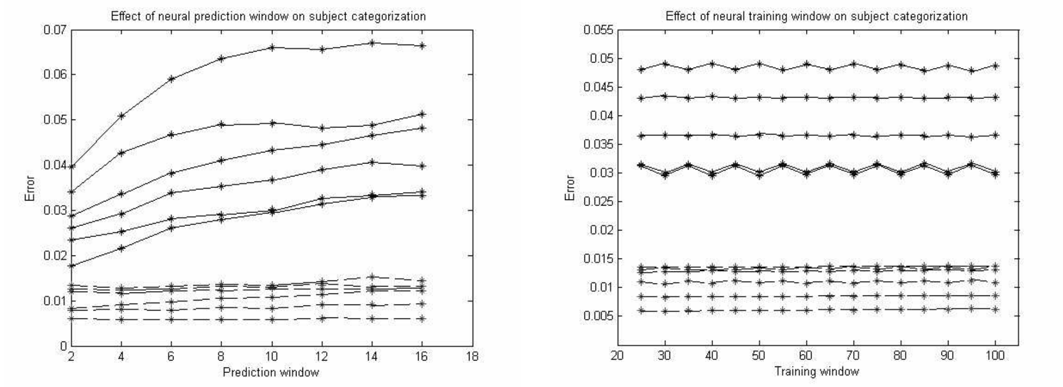


Figure 1: Histogram of the error of the neural network prediction. Solid lines represent the healthy subjects and the dashed the unhealthy ones.

As illustrated above, the solid lines represent the healthy subjects and the dashed the unhealthy ones. The differentiation between the two groups is distinct. According to physiology and as explained earlier, we expect that the cardiograms of the unhealthy subjects would be easier to predict, resulting in a small error. This is indeed the case, as is verified in the above figure, since the depicted error histogram displays a large concentration of error occurrences in the smaller bins. On the other had, the cardiograms of the healthy subjects should be more difficult to predict, thus resulting in greater errors. This is also verified in the figure, since this time the histogram shows a more even concentration of the error occurrences among all bins, indicating that there were similar amounts of small errors as there were large ones. This leads to the observed shape of the graph, where the plots of the unhealthy subjects begin at a much higher level than the healthy ones and rapidly drop to zero early on. In contrast, the plots of the healthy subject data begin at a lower point and decrease slightly through the entire graph.

The next step in understanding this behaviour is by investigating the mean prediction error. This is done by computing the mean differences between all the actual cardiogram data and the corresponding predicted ones. Although this is a very simple measure, its application produces satisfactory results. This measure as well as the above diagram is dependent on two factors: the prediction window and the training window. The latter is the size of the window that is used during training of the neural network. The former is number of points that are predicted in each step. It is of interest to examine whether and how the value of these windows influences the quality of subject categorization. The only way to determine this is through experimentation. The corresponding outcomes are illustrated in Figure 2.



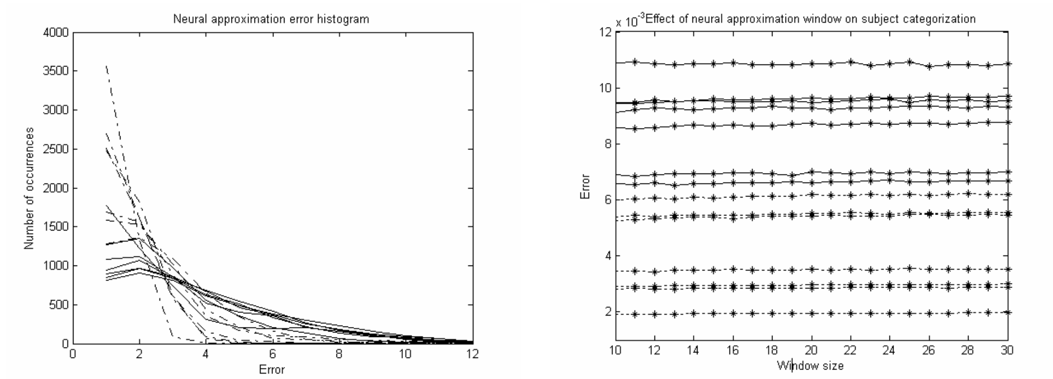
(a) (b)

Figure 2: In both figures the solid lines represent the healthy subjects and the dashed the unhealthy ones. (a) Plot of the mean prediction error for different prediction window sizes. (b) Plot of the mean prediction error for different training window sizes.

Figure 2(a) shows how the mean prediction error is affected by the size of the prediction window. The training window used in this case was equal to 50. Figure 2(b) depicts how the mean prediction error is affected by the size of the training window. In this case the prediction window is equal to 15. It is apparent that a good value for the prediction window is 15, while the size of the training window does not significantly alter the quality of the differentiation between the two groups. At this point we should note that in Figure 1 the prediction window applied was 15 and the training window was 50.

NEURAL NETWORK APPROXIMATION

The approximation results of the application of the radial basis function network to our healthy and unhealthy subject data is depicted in Figure 3.



(a) (b)

Figure 3: In both figures solid lines represent the healthy subjects and the dashed the unhealthy ones. (a)Histogram of the error of the neural network approximation. (b) Plot of neural network approximation for various sliding window values.

The solid lines represent the healthy subjects and the dashed the unhealthy ones. Figure 3(a) illustrates the differentiation between the two groups. In this case it is not as clear as it was when the network was used for prediction, but it is still satisfactory. Once again, the slope of the unhealthy data decreases more rapidly than that of the healthy data. Since this time the method is neural approximation, the approximation and training windows are equal. Thus a sliding window is the only parameter that is left to investigate. Figure 3 (b) shows that for reasonable sliding window values the results are not affected.

FUZZY LOGIC APPROXIMATION

The approximation result of the application of the ANFIS to our healthy and unhealthy subject data is depicted in Figure 4.

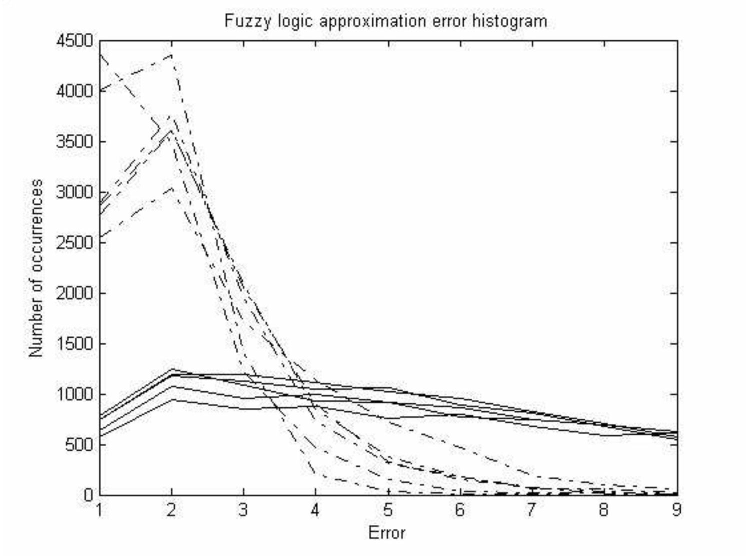
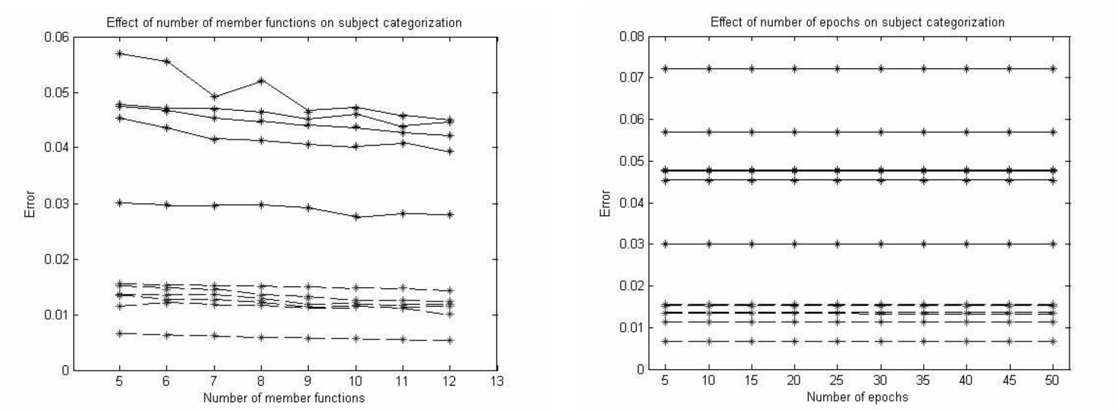


Figure 4: Histogram of the error of the fussy logic approximation. Solid lines represent the healthy subjects and the dashed the unhealthy ones

Once again, the general conclusions are similar to those discussed above. It is crucial to note that the differentiation between the two groups using this method is much improved and very clear. In this method there are two parameters to examine, which are the number of member functions used and the epochs, which are the number of cases used in training. Figure 5 indicates that both parameters do not significantly alter the clarity of differentiation between the two subject groups.



(a) (b)

Figure 5: In both figures solid lines represent the healthy subjects and the dashed the unhealthy ones. (a) Plot of the effect of the number of member functions on the resulting mean approximation error. (b) Plot of the effect of the number of epochs on the resulting mean approximation error

CONCLUSIONS

The results of this study indicate that both neural network prediction/approximation and fussy logic approximation methods do provide a clear separation between the cardiograms of healthy subjects and those of unhealthy subjects. The best distinction is achieved with neural prediction and fuzzy approximation, the latter being the best of the two. All of these results are in accordance to the physiological basis that the heart rate of a healthy individual is more erratic and therefore more difficult to forecast than that of an unhealthy subject.

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