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Multi Neural Networks Investigation Based Sleep Apnea Prediction

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Abstract

Sleep apnea (SA) is recognized as the most important and common type of sleep disorders with several short term and long term side effects on health and prediction of sleep apnea events before they happened can help to prevent these side effects. There are several studies on automated SA detection but not too much works have been done on prediction of apnea's individual episodes. This paper investigated the application of artificial neural networks (ANNs) to predict sleep apnea. Three types of neural networks were investigated: Elman, RBF and feed-forward back propagation on data from 5 patients. Based on the obtained results, generally on all of experiments the best performance is obtained by the feed-forward neural network with average of Area-Under-Curve (AUC) statistic equal to 0.866. But this superiority was not hold in all individual experiments and each of neural networks were be able to obtain the best result in some cases. This result showed the necessary of more investigation on methods such as dynamic neural networks selections instead of using a fixed model.

"Keywords: Sleep apnea; Neural network; prediction"

1. Introduction

Sleep apnea (SA) is one of the most common types of sleep disorders with around 3% prevalence in industrialized countries [1]. SA is characterized by a repeated and temporary cessation or reduction of breathing during sleep. Clinically, apnea is defined as the total or near-total absence of airflow. This reduction becomes significant once the decline of the breathing signal amplitude is at least around 75% with respect to the normal respiration and occurs for a period of 10 seconds or longer [2].

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Sleep apnea has several short term and long term side effects [3]. Short-term effects can lead to impaired attention and concentration, reduce quality of life, increased rates of absenteeism with reduced productivity, and increased the possibility of accidents at work, home or on the road. Long-term consequences of sleep deprivation include increased morbidity and mortality from increasing automobile accidents, coronary artery disease, heart failure, high blood pressure, obesity, type 2 diabetes mellitus, stroke and memory impairment as well as depression. Long-term consequences, however, remain open [3]. Prediction of sleep apnea events before they happened can help to prose an approaches to prevent these events before they happen.

There are several works on applications of predicting in different areas, but there are few studies in sleep apnea prediction. One of the earliest works in this area is paper of Dagum and Galper in 1995 [4]. This paper developed a time series prediction by using belief networks models. This paper used a multivariate data set contains of heart rate (HR), chest volume (CV), blood oxygen concentration (SaO2), and sleep state. Based on this study, prediction with the CV signal has more bias than HR and SaO2, because of rapid and erratic oscillations of the CV series.

Another pioneer work in sleep apnea prediction can be found in the paper of Bock and Gough paper in 1998 [5]. This study used heart rate, respiration force, and blood oxygen saturation (SaO2.) They used simple recurrent networks (SRN) proposed by Elman [6]. Each of three time series variables (heart rate, breathing, and blood oxygenation) were used as inputs for network training and testing operations. Each variable was introduced to a unique network node at the input layer; this network had 18 nodes in the hidden layer.

The newest paper in this area is the work of Waxaman, Graupe and Carley in 2010 [7]. They predicted apnea from 30 to 120 seconds in advance. They use LArge Memory STorage and Retrieval (LAMSTAR) neural network. LAMSTAR is a supervised neural network that can process large amount of data and also provide detailed information about its decision making process. Input signals for this algorithm are EEG, heart rate variability (HRV), nasal pressure, nasal temperature, submental EMG, and electrooculography (EOG). They trained separate LAMSTAR for each of 30, 60, 90 and 120 seconds segment. Results showed that best prediction belongs to next 30 seconds and they obtained lower performance for longer lead time, however, most of predictions up to 60 seconds in the future were correct.

This article is to compare the sleep apnea prediction performance of three different neural networks, Elman, Radial Basis Function (RBF) network and Feed-Forward (FF) back propagation. The main aim of this article is to investigate the possibility of choosing a fixed neural network for all experiments as the best model. This study can fill the gap in previous studies that used a fixed model for all of the experiments in their research. In the rest of this paper, the proposed method comprised of the issues related to network design and training, especially how to avoid over fitting and the performance measure are addressed. The results and conclusions are presented at the end of the paper.

2. Proposed Approach

In this paper, three input signals; airflow, abdominal and thoracic movement signals, are used based on what had been found in our previous work as the most important signals for SA studies [8]. In the present work data collected from 5 patients were collected in the concord hospital in Sydney which SA events are annotated by an expert. In this paper we used 30, 60, 90, and 120 seconds segments to predict various lead times (30, 60, 90 and 120 seconds into the future). In this article, for the performance index, AUC or Area under ROC curve is considered, by computing area under plotting of the sensitivity versus the false positive rate, or l-specificity, for varying cut-off values. Unlike classification accuracy, ROC is independent of class distributions or error costs and has been widely used in the biomedical field especially when assumptions of equal misclassification costs and constant class distribution in the target environment are not hold. The AUC can be statistically interpreted as the probability of the classifier to correctly classify and the higher AUC means the better classification performances.

2.1. Features generation

Each signal was normalized through dividing by its mean value and then for each segmentation windows variety of features were extracted from the nasal airflow, abdominal and thoracic movement signals. Features are generated from coefficients of wavelet packet and the original signals. Haar wavelet packet with 3 levels is used and different statistical measures are generated from the coefficients of the wavelet. These features represent the inputs of the NNs algorithm. Finally all input features values were rescaled within the range [-1, 1]. Full list of proposed features are included in the Table I. By this approach 60 features are generated for each segment windows.

Table I: List of statistical features, x is coefficients of wavelet packet.

$\log(\mathrm{mean}(x^2))$	$\mathrm{kurtosis}(x^2)$	$\mathrm{geomean}(\lvert x\rvert)$
$\mathrm{std}(x^2)$	$\mathrm{var}(x^2)$	$\mathrm{mad}(x)$
$\mathrm{skewness}(x^2)$	$\mathrm{mean}(\lvert x\rvert)$	$\mathrm{mean}(x^2)$
$\mathrm{skewness}(x)$	$\mathrm{kurtosis}(x)$	$\mathrm{var}(x)$
$\mathrm{geomean}(x^2)$	$\mathrm{mad}(x^2)$	$\mathrm{std}(x)$

More details about these statistical measures are presented in the Appendix A.

2.2. Neural Networks

Three different NNs; Elman, radial basis function network and feed-forward back propagation, are used for sleep apnea prediction. For the Elman and feed-forward NNs, Log-sigmoid and pure-line are selected as transfer functions of the hidden layer and the output layer, respectively. Scaled conjugate gradient back propagation is selected as the training function, for these three NNs. Number of nodes in the hidden layer of each NN are determined by trial and error; more details about architecture of NNs are explained in the experimental section. Also, number of nodes in the input layer is 60, equal to the number of features.

In this study, we want to predict sleep apnea in the next 30, 60, 90 and 120 seconds. The prediction is based on investigation of various lengths of segment windows from 30 seconds to 120 seconds. For each of these experiments a unique NN is trained.

2.3. Early Stopping

Standard neural network architectures such as the fully connected multi-layer perceptron are prone to over fitting. While the network seems to get better and better (the error on the training set decreases), at some point during training it actually begins to get worse again, (the error on unseen examples increases).

There are two basic ways to overcome the over fitting problem which are; reducing the number of dimensions of the parameter space or reducing the effective size of each dimension. The corresponding NN techniques for reducing the size of each parameter dimension are regularization such as weight decay or early stopping [9]. Early stopping is widely applied because it is simple to understand and implement and has been reported to be superior to regularization methods in many cases. Early stopping can be used either interactively, i.e. based on human judgment, or automatically, i.e. based on some formal stopping criterion. In this paper, automatic stopping criteria based on the cross validation error is used and the validation error is used as an estimate of the generalization error [9].

3. Results and discussion

For determining the best number of nodes in the hidden layer of each neural network, AUC of different architectures are computed for one of the patients. Results are as Figure 1, in this figure AUCs for predicting 30 seconds into the future by using 30-second segments are plotted for various architectures. Based on these results, numbers of hidden nodes are selected as 40, 110 and 50 for Elman, RBF and FF, respectively.

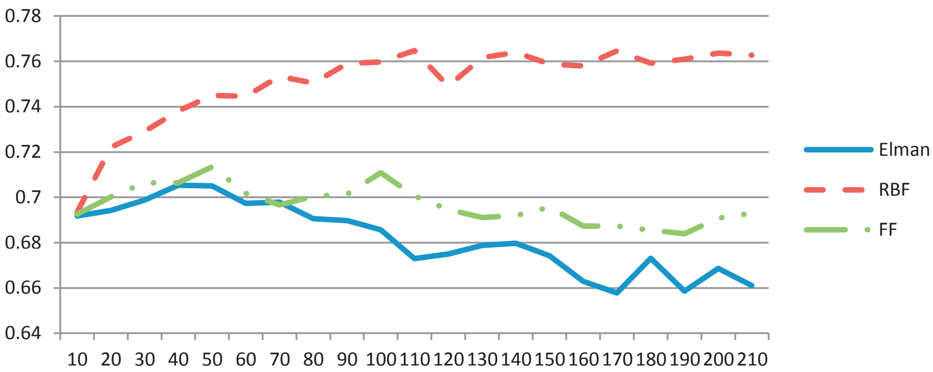
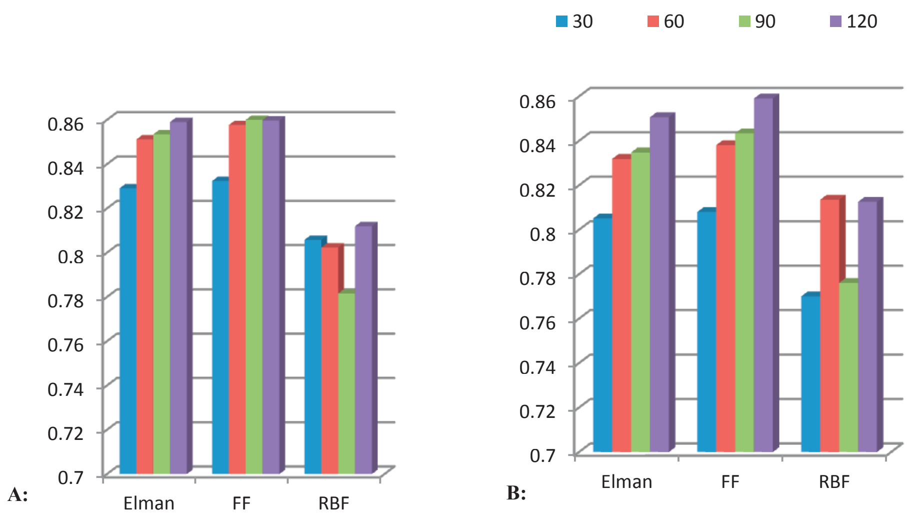
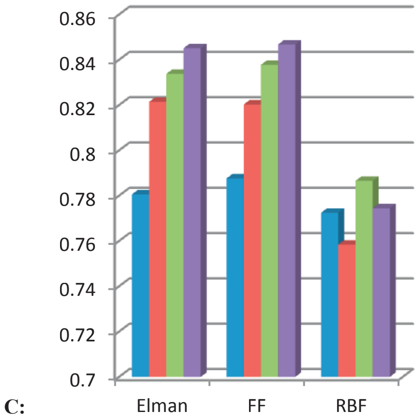


Figure 1: AUC versus number of nodes in the hidden layer

By attention to the final architectures, 10 experiments are done for each of prediction using 30, 60, 90 and 120 second windows for prediction of 30, 60, 90 and 120 seconds into the future on each of the five patients. Figure 2, shows the results of using Elman, FF and RBF neural networks. Based on these results, for the 30-second lead time (figure 2. A) the best result is obtained with using the FF and 90 seconds segments by average AUC equal to 0.8662±0.05, while the best AUC of Elman and RBF are obtained as 0.8590±0.06 and 0.8119±0.15 by using the 120 seconds segments. For the 60-second lead time prediction (figure 2. B) the best result is obtained by using FF again, but by using the 120 seconds segments equal to 0.8590±0.06, and the best results of the Elman and RBF are as 0.8505±0.07 and 0.8134±0.12 with using 120 seconds segments.





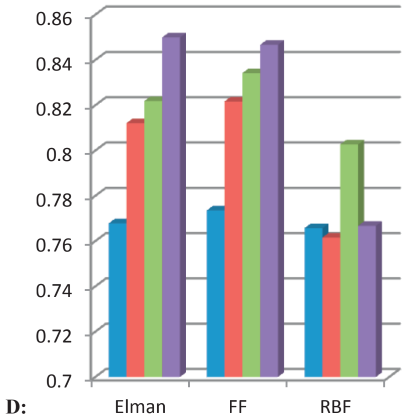


Figure 2. Results of using 30-second, 60-second, 90-second and 120-second segments with Elman, FF and RBF NNs for sleep apnea prediction into future (A) 30 seconds, (B) 60 seconds, (C) 90 seconds and (D) 120.

For the 90-second lead time prediction (figure 2. C) again the best result is obtained with using the FF and by using 120 seconds segments equal to 0.8467±0.06, and the best results of Elman and RBF are as 0.8450±0.07 and 0.7744±0.16 with using 120 seconds segments, respectively. Finally, for the 120-second lead time prediction (figure 2. D) the best result is obtained with using the Elman and 120 seconds segments, 0.8499±0.07, and the best results of FF and RBF are as 0.8466±0.07 and 0.8026±0.12 with using 120 seconds and 90 seconds segments, respectively.

If we look at AUCs obtained by different segment windows, we can see that the averages of AUC of them are not same and ANOVA test also shows that difference between these averages is significant. Generally, by attention to the results, as the segmented windows increased the performance is also increased. Also based on the figure 2 it is obvious that as the lead time increased the performance is decreased.

By considering these results and if we deliberate all of the experiments, then the average of the AUC for Elman, FF and RBF are as 0.8279,0.8332 and 0.7851 it is obvious that the performance of RBF is the lowest and the t-test shows that even the difference between FF and the Elman is significance. Hence we can rank these NNs based on their performances as FF, Elman and RBF. But if we look at the results of 5 patients separately then different result can be obtained. Table 2 tabulated the best NN model and the best segmented windows length for the considered lead time for the 5 patients separately.

	Lead time			
patient	**30 second**	**60 second**	**90 second**	**120 second**
#1	RBF (90 seconds)	RBF (120 seconds)	RBF (90 seconds)	RBF (120 seconds)
#2	FF (90 seconds)	Elman (120 seconds)	Elman (120 seconds)	Elman (120 seconds)
#3	FF (90 seconds)	FF (120 seconds)	FF (120 seconds)	Elman (120 seconds)
#4	RBF (120 seconds)	RBF (120 seconds)	RBF (120 seconds)	RBF (90 seconds)
#5	RBF (60 seconds)	RBF (120 seconds)	RBF (90 seconds)	Elman (120 seconds)

Table 2. Best NN model and the best segmented windows length for each of the lead time and for the 5 patients separately.

Table 2 shows that different setting is optimal for different patients and lead time, and there is not any unique optimal model for these experiments. By attention to this result, nested methods and dynamic neural models selection methods [10] should be considered in the future studies to selecting the best model for each experiment.

4. Conclusion

In this study, we present a step of an ongoing investigation into the prediction of individual events of sleep apnea with different artificial neural networks. Experimental results of Elman, RBF and feed-forward back propagation neural networks shows that, increasing the lead time can improve the performances, in the most cases and generally the best result is obtained by the feed-forward neural network with average AUC equal to 0.8662 . But if we pay attention to the individual patients or different lead times or segmentation windows then for each experiment a different neural model can obtain the best result. Therefore investigation on ensemble NNs and also dynamic model selection should be considered in the future works.

Appendix A.

Mean, variance (VAR) and standard deviation (STD) are common and well known statistical tools, so other statistical features, in this study, are reviewed here.

Kurtosis: The kurtosis of a distribution is a measure of how outlier-prone a distribution is, and defined as follow

$$k = \frac{E(x-\mu)^4}{\sigma^4}$$

Geomean: Geomean is the geometric mean and computed as follow:

$$m = \left[\prod_{i=1}^{n} x_i\right]^{1/n}$$

Skewness: Skewness is a measure of the asymmetry of the data around the sample mean, and defined as follow

$$s = \frac{E(x-\mu)^3}{\sigma^3}$$

Mad: mad is mean absolute deviation of the sample as, $mean(|(x - mean(x))|)$.

References

1. Young, T., M. Palta, J. Dempsey, J. Skatrud, S. Weber, and S. Badr, THE OCCURRENCE OF SLEEP-DISORDERED BREATHING AMONG MIDDLE-AGED ADULTS. New England Journal of Medicine, 1993. 328(17): p. 1230-1235.
2. Guilleminault, C., Clinical overview of the sleep apnea syndromes. Sleep Apnea Syndromes, 1978: p. 1-12.
3. Sleep-related breathing disorders in adults: recommendations for syndrome definition and measurement techniques in clinical research. The Report of an American Academy of Sleep Medicine Task Force. Sleep, 1999. 22(5): p. 667-89.
4. Dagum, P. and A. Galper, TIME-SERIES PREDICTION USING BELIEF NETWORK MODELS. International Journal of Human-Computer Studies, 1995. 42(6): p. 617-632.
5. Bock, J. and D.A. Gough, Toward prediction of physiological state signals in sleep apnea. Ieee Transactions on Biomedical Engineering, 1998. 45(11): p. 1332-1341.
6. Elman, J.L., DISTRIBUTED REPRESENTATIONS, SIMPLE RECURRENT NETWORKS, AND GRAMMATICAL STRUCTURE. Machine Learning, 1991. 7(2-3): p. 195-225.
7. Waxman, J.A., D. Graupe, and D.W. Carley, Automated Prediction of Apnea and Hypopnea, Using a LAMSTAR Artificial Neural Network. American Journal of Respiratory and Critical Care Medicine, 2010. 181(7): p. 727-733.
8. Maali, Y. and A. Al-Jumaily, Signal Selection for Sleep Apnea Classification, in AI 2012: Advances in Artificial Intelligence, M. Thielscher and D. Zhang, Editors. 2012, Springer Berlin Heidelberg. p. 661-671.
9. Prechelt, L., Automatic early stopping using cross validation: quantifying the criteria. Neural Networks, 1998. 11(4): p. 761-767.
10. Li, Y., D.F. Wang, P. Han, and Ieee, A DYNAMIC SELECTIVE NEURAL NETWORK ENSEMBLE METHOD FOR FAULT DIAGNOSIS OF STEAM TURBINE. Proceedings of 2009 International Conference on Machine Learning and Cybernetics, Vols 1-62009. 1-6.