Automated Detection of Obstructive Sleep Apnoea by Single-lead ECG through ELM Classification

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Abstract

This study aims to provide automated screening of obstructive sleep apnoea (OSA) by ECG signal processing. Using ECG as an OSA diagnosis tool is an attractive alternative as it is low-cost and the diagnostic test can be performed at home.

Single-lead ECG recordings were used to detect apnoeic events through a minute-by-minute analysis. The MIT PhysioNet Apnea-ECG database was used. It contains 70 overnight ECG recordings from normal and obstructive sleep apnoea patients. Thirty-five recordings were used for training data and the other 35 for testing. Time and frequency domain features were obtained. Classification was achieved with an Extreme Learning Machine (ELM) as it provided a flexible non-linear classifier that was fast to train.

Classification accuracy was obtained with the hidden-layer neurons per input (fan-out) varying between 1 and 10. The highest accuracy was 87.7%, at a fan-out of 10, with specificity of 91.7% and sensitivity of 81.3%. Our results were comparable with other published systems using the Apnea-ECG database. OSA can be diagnosed from a single-lead ECG with a high degree of accuracy.

1. Introduction

Sleep disorders are a prevalent health issue, which are currently costly and inconvenient to diagnose as they normally require an overnight hospital stay by the patient. Obstructive Sleep Apnoea (OSA) is a prevailing sleep related respiratory disorder that reduces or causes a total pause of airflow accompanied by continuous attempt to breathe. It is identified by frequent collapse of the upper airway during sleep along with interruption of breathing which causes blood oxygen desaturation and consequently, sleep arousals [1][2].

Guilleminault [3] initially defined OSA to be associated with at least 10 seconds of pause in breath. Currently, apnoea severity is measured with the apnoea-hypopnea index (AHI) which is the average number of apnoea and hypopnea events per hour. If AHI is greater than 5, the patient is considered to be at risk for OSA [2].

Smokers, alcohol consumers, middle-aged and older men, post-menopausal women, overweight and obese people, those with larger neck sizes or with family history of OSA are among groups with higher risk of OSA [2][4] [5]. Also, it has been reported that pregnancy may cause OSA in women [6]. Around 1 in 20 adults suffer from OSA syndrome, which is OSA with daytime effects. They mostly remain undiagnosed. In addition, it is estimated that one in five adults endure minimally symptomatic or asymptomatic OSA which is scarcely diagnosed [6].

Previous population-based epidemiologic studies revealed extensive range of undiagnosed obstructive sleep apnoea. They also have demonstrated that even mild obstructive sleep apnoea can be a cause of serious diseases [6]. Eighty to nighty percent of adults never get diagnosed. Untreated OSA may lead to serious health issues such as cardiovascular disease, hypertension and stroke. Furthermore, the resulting daytime tiredness and sleepiness may lead to workplace and road accidents. As a result, diagnosis and treatment of OSA is important for both patients and society to reduce the health costs [7]. There is no doubt about the necessity of developing simpler diagnosis and treatment for OSA, but proposing reliable methods of OSA diagnosis is still contentious [6].

The traditional and standard method of sleep diagnosis is a sleep study which is called polysomnogram (PSG). It is a multi-channel recording of sleep state as well as recording electrocardiography (ECG), electrooculography (EOG), electromyography (EMG), oxygen saturation, electroencephalography (EEG), oronasal airflow and respiratory measurement. Patients need to stay for at least a night in hospital or sleep laboratories for a sleep test [2] [8] [5]. The test has two major problems: firstly, it is expensive as it needs overnight specialized staff and facilities. Secondly, it requires long waiting time because of limited resources [7]. Moreover, the standard sleep test needs the attachment of wires and electrodes which disturb the patient's sleep. The patients also may have issues with falling asleep in the unknown environment. As a result, many patients prefer to go through a home based sleep test which can reduce the financial cost, the waiting time, and provide a convenient sleep environment [7].

Implementing simpler and fewer signals could be beneficial in development of new sleep diagnosis systems. This may lead to the use of less invasive sensors and reduce interference of sleep [9]. For instance, using ECG as an OSA diagnosis tool is an attractive alternative as it is low-cost and the diagnostic test can be performed at home. In this paper, single-lead ECG recordings were used to detect apnoeic events through a minute-by-minute analysis. Time and frequency domain features were obtained. Classification was achieved with an Extreme Learning Machine (ELM) which is a flexible non-linear classifier and fast to train.

2. Input data

The MIT PhysioNet Apnea-ECG database was used. The recording has been done by the standard sleep laboratory with a modified lead V2 position ECG. It comprises 70 overnight ECG recordings from normal and obstructive sleep apnoea patients. The length of the single-lead ECG signal is between 401 to 578 minutes and the sampling rate is 100 Hz. There are 34313 minutes of recording as the whole database. There were 32 subjects consisting 25 men and 7 female [8]. Thirty-five recordings were implemented for training data as they are presented with minute-by-minute apnoea annotations and the other 35 for testing [10][11].

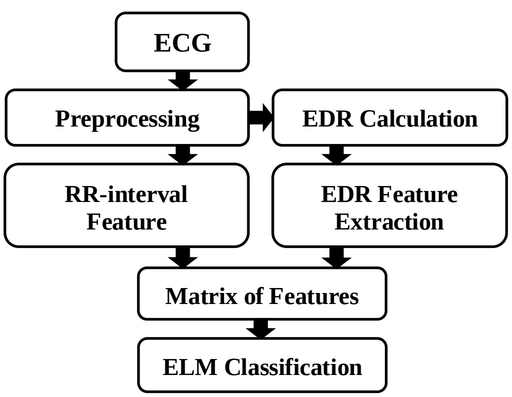

Figure 1. Schematic representation of automatic OSA detection.

3. Method

First, preprocessing has been applied to the input data. It consists of data cleaning procedure including the baseline wander and high frequency noise removal. Baseline wander has been removed by applying two median filters with 200-ms and 600-ms width to the ECG input signal [9].

3.1. QRS Detection

The QRS times of the cleaned ECG were detected. They are defined as the onset times of QRS complex and the peak occurrence and were achieved by a single scan of an automatic QRS detection algorithm proposed in [12]. RR intervals series were calculated as the difference between two adjacent QRS time points.

Next, a QRS revision and interpolation algorithm has been applied to the QRS detections [9] to remove false and interpolate missed QRS detections. This procedure was a part of ECG noise reduction since noise is an inevitable component of ECG signal recording. An automatic algorithm has been used which compares each pair of QRS or corresponding RR interval to a Robust RR value [9]. This Robust RR interval was obtained by applying a median filter with 5 sec width to RR sequence. It gives a robust measure of the local tendency of the RR sequence. By comparing adjacent RR intervals with Robust RR value, the missed and false QRS times can be identified. Then, the algorithm ignores the outlier or interpolates the QRS times. It leads to a more reasonable set of QRS times and RR interval sequence.

3.2. Feature Extraction

A set of time and frequency features was extracted from the QRS and RR interval sequence derived above. The selected features in this study were mean, standard deviation and power spectral density (PSD) of RR interval and ECG-Derived Respiratory (EDR) signal [13].

Power spectral density of RR intervals was estimated for each 1-minute epoch of RR interval series against the index of samples or beats. Firstly, it was zero padded to 256 points and fast Fourier transform (FFT) was applied. Then the mean value was removed and the squared magnitude of FFT coefficients was calculated. Then, the average of each four frequency bins was measured. Half of the resulting 64 points did not provide further information as it has a symmetrical pattern. Therefore, the first 32 points were used as PSD features for each 1-minute epoch [9].

The same features were generated from ECG Derived Respiratory (EDR) signal. It is a modulation signal resulting from respiration that affects the amplitude of ECG signal. There are different definitions for EDR measurement [14]. In this study, the bound region of the cleaned ECG was computed in a 100-ms window after the QRS detection peaks [14][15]. Then, EDR signal was modified by discovering the outliers. Initially, a median filter with 110-ms window width has been applied to EDR signal and it was subtracted from EDR. Then, the points in 10 times beyond 75% and 10 times less than 25% of the signal were labelled as outliers and were eliminated.

Mean value, standard deviation and power spectral density (PSD) of modified EDR were measured for each 1 minute epoch [13]. Finally, a mean value, a standard deviation and 32 PSD features were generated for both RR interval and EDR signal. A log transform was applied to all of the features as the histogram of the resulting features more closely approximated a Gaussian curve.

The final step was to rescale all training data features so that they had zero mean and a variance of 1 when evaluated across all of the data. All test data was rescaled using the same scaling factors.

3.3. ELM Classifier

The matrix of 68 features of both RR interval series and EDR signal for the whole record was applied as the input to the classifier. Classification was done by an Extreme Learning Machine (ELM). It is a flexible non-linear classifier and is fast to train. The ELM is feed-forward network with one hidden layer. The input layer signals are connected to a large number of non-linear hidden neurons, using randomly initialized connection weights. The proportion of the number of hidden layer neurons to input layer neurons is called “fan-out” number [16]. The output neurons are linear and the optimising values for the output weights can be simply achieved in a single iteration. The term “extreme” is due to the network’s higher speed in classification, better generalization and less training error. It can be easily and quickly performed and test results on many standard sets has shown very good performance [17].

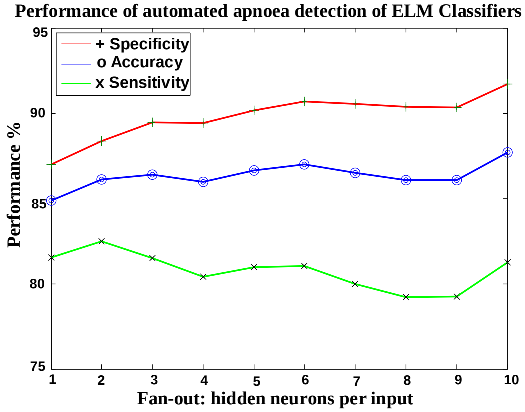

Figure 2. Performance results of ELM classifier.

Input layer weights were set to random values between -1.5 to 1.5. Tanh function was chosen as activation function of hidden layers, as it can be easily implemented in hardware. The hidden layer weights were produced in a single iteration by calculation of the pseudoinverse of hidden layer activations values and multiplying by the target values of the outputs [16].

4. Results

The network was trained using the 35 training records of the database. The performance of the network was evaluated using the 35 test records (x01..x35.*).

Classification accuracy was obtained with the hidden-layer neurons per input (fan-out) varying between 1 and 10. The highest accuracy was 87.7%, at a fan-out of 10, with specificity of 91.7% and sensitivity of 81.3%. Classification performance results for fan-out of 1 to 10 are shown in table 1.

Table 1. Classification performance for different fan-outs.

Fan-out	Accuracy(%)	Specificity(%)	Sensitivity(%)
1	84.9	87.1	81.5
2	86.1	88.4	82.5
3	86.4	89.4	81.5
4	86.1	89.4	80.4
5	86.6	90.2	81.1
6	87.1	90.7	81.1
7	86.5	90.5	80.1
8	86.1	90.4	79.2
9	86.1	90.3	79.2
10	87.7	91.7	81.3

5. Discussion

The performance of ELM classifier in the proposed automated detection of sleep apnoea by ECG signal was comparable to the results of other algorithms with the same ECG database as the input.

In a comparison research of automatic and visual inspection algorithms of apnoea detection, different frequency and time domain features and different transformations were used [8]. The highest accuracy of 92% was achieved by two teams that used manually verification of apnoeic events.

An autoregressive model using the same database and features obtained the accuracy of approximately 86% [15].

Another study on apnoea detection used combination of a number of classifiers such as AdaBoost, Decision Stump, Bagging and SVM as well as feature selection on ECG features and SPO_2 features [18]. They compared the performance results of various combinations of classifiers and feature sets. They reported the highest accuracy of combination of classifiers on the combined feature set to be 84.4% with the highest specificity of 85.9%.

6. Conclusion

An automated algorithm to detect apnoeic epochs of ECG signal using ELM claffifier has been proposed. Our results were comparable with other published systems using the Apnea-ECG database. OSA can be diagnosed from a single-lead ECG with a high degree of accuracy through this system. Future work may include using other non-linear function for hidden layer neurons and also using larger fan-out numbers.

Acknowledgements

This work was supported by ARC grant FT110101098 and the UWS scholarship support program.

References

[1] Chaska B. , Suratt P. M. et al, "SLEEP A PNEA : Is Your Patient At Risk", *NIH Publ.*, National Institutes of Health, National Heart, Lung and Blood Institute, 1995, vol. 95–3803, pp. 1-10.

[2] FlemonsW. Ward, Buysse Daniel, Redline Susan et al., "Sleep – Related Breathing Disorders in Adults : Recommendations for Syndrome Definition and Measurement Techniques in Clinical Research," , E. R. Society , *Sleep*, 1999, vol. 22, no. 5, pp. 667–689.

[3] Gulleminault C., Lehrman A. T., Forno L., and Dement W. C., "Sleep apnoea syndrome: states of sleep and autonomic dysfunction.," *J. Neurol. Neurosurg. Psychiatry*, Jul. 1977, vol. 40, no. 7, pp. 718–25.

[4] American Academy of Sleep Medicine, "Obstructive Sleep Apnea" , 2008, *AASM*.

[5] Whitelaw William A., Burgess Keith R., "Diagnosis of Sleep apnoea: some critical issues." Indian J Med Res, 2010, 131, pp. 217–229.

[6] Young T., Peppard P. E., and Gottlieb D. J., "Epidemiology of Obstructive Sleep Apnea," *Am. J. Respir. Crit. Care Med.*, May 2002, vol. 165, no. 9, pp. 1217–1239.

[7] Allen R. K. A., "Home sleep studies," *Aust. Prescr.*, 2012, vol. 35, no. 2, pp. 62–4.

[8] Penzel T., McNames J., Murray A, de Chazal P., Moody T., and Raymond B., "Systematic comparison of different algorithms for apnoea detection based on electrocardiogram recordings.," *Med. Biol. Eng. Comput.*, Jul. 2002, vol. 40, no. 4, pp. 402–7.

[9] de Chazal P., Heneghan C., Sheridan E., Reilly R., Nolan P., and O'Malley M., "Automated processing of the single-lead electrocardiogram for the detection of obstructive sleep apnoea.," *IEEE Trans. Biomed. Eng.*, Jun. 2003, vol. 50, no. 6, pp. 686–96.

[10] Penzel T., Rg G. B. M., Goldberges M. A. L., and Peter H., "The Apnea-ECG Database," *Comput. Cardiol. 2000*, 2000,*Vol.27*, vol. 27, pp. 255–258.

[11] Goldberger A. L., Amaral L. A. N., L. Glass, J. M. Hausdorff, P. C. Ivanov, R. G. Mark, J. E. Mietus, G. B. Moody, C.-K. Peng, and H. E. Stanley, "PhysioBank, PhysioToolkit, and PhysioNet : Components of a New Research Resource for Complex Physiologic Signals," *Circulation*, Jun. 2000, vol. 101, no. 23, pp. e215–e220.

[12] Engelse W. A. H., Zeelenberg C., "A single scan algorithm for QRS-detection and feature extraction", *Computers in Cardiology*, 1979, Vol. 6, pp. 37-42.

[13] De Chazal P., Reilly R., and Heneghan C., "Automatic Sleep Apnoea Detection using Measures of Amplitude and Heart Rate Variability from the Electrocardiogram," *IEEE*, 2002, vol. 1, pp. 775–778.

[14] O'Brien C. and Heneghan C., "A comparison of algorithms for estimation of a respiratory signal from the surface electrocardiogram.," *Comput. Biol. Med.*, Mar. 2007, vol. 37, no. 3, pp. 305–14.

[15] Mendez M. O., Ruini D. , Villantieri O. P., Matteucci M., Penzel T., Cerutti S., and Bianchi A. M., "Detection of sleep apnea from surface ECG based on features extracted by an autoregressive model.," *Conf. Proc. IEEE Eng. Med. Biol. Soc.* , Jan. 2007, vol. 2007, pp. 6106–9.

[16] Tapson J. and Van Schaik A., "Learning the pseudoinverse solution to network weights," *Neural Networks*, 2013, vol 45, pp. 94–100.

[17] Huang G. B., Zhu Q. Y., and Siew C. K., "Extreme learning machine: Theory and applications," *Neurocomputing*, Dec. 2006, vol. 70, no. 1–3, pp. 489–501.

[18] Xie B. and Minn H., "Real-time sleep apnea detection by classifier combination.," *IEEE Trans. Inf. Technol. Biomed.*, May 2012, vol. 16, no. 3, pp. 469–77.

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