International Journal of Electrical and Electronics Engineers
Vol. No. 9, Issue No. 01, January-June 2017
ISSN (O) 2321-2055
ISSN (P) 2321-2045

DETECTION OF SLEEP APNEA USING ECG SIGNAL ANALYSIS

Dhale Prachi Rajaram[1], Prof.Borate S.P[2]

[1,2] Dept. of Electronics and Telecommunication, SVPM COE,Malegaon BK, Baramati,Pune

ABSTRACT

To find efficient and valid alternative to Polysomnography, an different method is presented in characterizing bio-signals for detecting epochs of sleep apnea with high accuracy . The signal which are related to breath defect; ECG is investigated, in order to extract physiological indicators that determines sleep apnea. the automated method used which analyzed ECG to find irregular heartbeats. The approach presented in this paper was tested using downloaded polysomnographic ECG data from the Physionet database. The system consists of three main parts which are signal segmentation, features extraction and features . For classification SVM classifier used which simply performs classification by constructing an n-dimensional hyperplane that optimally separates the data into two classes, which gives the result SA is positive or negative.

Keywords: Apnea monitor, ECG, support vector machines (SVMs).

I. INTRODUCTION

Sleep is the circadian rhythm which is essential for human life. Humans spend approximately one-third of their life to sleep. Sleep is necessary for optimal health, as the person sleeps, his body repairs itself. Blood pressure fluctuates, heart rate slows down, hormone fluctuates, muscles and other tissues relax and repair and the replacement of aging or dead cells occur during sleep. Without sleeping, the humans do not function as well as they can. A sleeping disorder takes place when one cannot sleep, causing the body to lose function. Sleep Apnea (SA) is becoming a more common cause of sleepiness in children and adults. It is characterized by abnormal pauses of breathing or abnormally low breath during sleep. These pauses of breathing can range in frequency and duration. The duration of the pause might be ten to thirty seconds.

The aim is to present, a method in characterizing bio-signal for detecting epochs of sleep apnea with high accuracy. The biosignal that are related to breath defect; ECG used to present this method. A model using the ECG signal features was developed and its effectiveness using the Apnea ECG database was evaluated, using different records available in that database. The model is based on a selective set of RR-interval based features that are given to a Support Vector Machines (SVM) for classification.The specific purposes of this system are: a) To eliminate the noise of the ECG; b) To use the wavelet's tool, producing the Hyponogram from the ECG signal;

The remainder of this paper is organized as follows. Section II describes the methodology used in this study, the preprocessing steps, the two algorithms implemented. The results are presented in Section III. Conclusions are presented in section IV.

International Journal of Electrical and Electronics Engineers
Vol. No. 9, Issue No. 01, January-June 2017
ISSN (O) 2321-2055
ISSN (P) 2321-2045

.

II. METHODOLOGY

A. Subjects Database

The device and algorithms were tested using Physionet Apnea-ECG Database. The database has a total of 35 subjects' sleep studies. The recordings were visually scored by an expert for sleep apnea/hypopnea events on the basis of respiration and oxygen on a per minute basis.

B. ECG

ECG is considered as one of the most efficient features to detect sleep disorders. Cyclic variations in the duration of a heart beat, also known as RR interval of ECG have been reported to be associated with sleep apnea episodes. RR-interval is defined as the time interval between two consecutive R peaks.

C. Data Preparation

To select the data, we chose the ECG records which have continuous apnea data for a certain period of time, followed by a regular (normal) data representation for a period of time, or vice versa. The data preparation is used for training the SVM classifier. The next step in our procedure after data selection is data partitioning. In our work, three cases of partitioning were analyzed, as follows:

- *Case* 1. The apnea and regular data are partitioned into 10 second pieces.
- *Case* 2. The apnea and regular data are partitioned into 15 second pieces.
- *Case* 3. The apnea and regular data are partitioned into epochs of 30 second pieces.

Since apnea is defined as a pause in breathing, and can last from a few seconds to minutes (almost >=10 sec); we investigate the three above cases to determine the best accuracy that can be achieved.

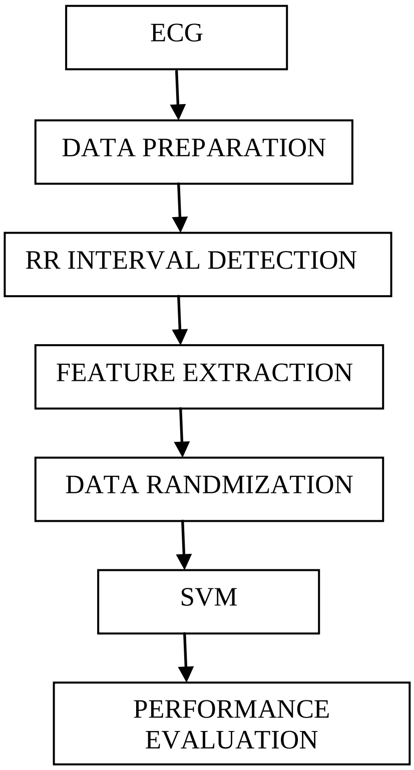

Fig 1.Schemaic Diagram of system

D. RR Interval Detection

We need to distinguish the R waves from the other waves of the ECG signal. Therefore, we developed the following two conditions, in which R-peak was detected. An R peak will be identified if both conditions 1 and 2 are satisfied.

1) It has to be a local maximum, which is detected by a local max function within a window of 200ms.

2 The detected local max peaks must be 10 times greater than the mean value.

Once the R-peak was extracted, RR intervals were calculated.

E. Features Extraction

The following ECG features which are most effective for apnea detection are calculated:

- Mean epoch and recording RR-interval.
- Standard deviation of the epoch and recording RR interval.
- The NN50 measure (variant 1), defined as the number of pairs of adjacent RR- intervals where the first RR interval exceeds the second RR- interval by more than 50 ms.
- The NN50 measure (variant 2)
- Two pNN50 measures, defined as each NN50 measure divided by the total number of RR intervals.
- The SDSD measures, defined as the standard deviation of the differences between adjacent RR- intervals.

F. Support Vector Machines

We use Support Vector Machines (SVM) as a classification (also known as supervised learning) method in order to investigate apneaic epoch detection. In our implementation, we use a linear kernel function to map the training data into kernel space. In the optimization process, we use a method called sequential minimal optimization to find the separating hyperplane. For data randomization, we separate the apnea and non apnea data. We then separate training data and testing data, with 80% for the training and 20% for the testing. After the signals are separated, we perform the training for SVM.

III. RESULT

We evaluated the effectiveness of our model on the different records in the Apnea-ECG database. MATLAB toolset was used for signal processing and classification. Two statistical indicators, Sensitivity (*Se*) and Specificity (*Sp*) in addition to the Accuracy (*Acc*) have been used to evaluate the performance of our classification system. The model is based on SVM classifier which uses various RR interval features of the ECG signal.

	Average of training set results		
Features	Accuracy	Sensitivity	Specificity
4	0.8625	0.8823	0.8473

Table 1

International Journal of Electrical and Electronics Engineers
Vol. No. 9, Issue No. 01, January-June 2017
ISSN (O) 2321-2055
ISSN (P) 2321-2045

	Average of testing set results		
Features	Accuracy	Sensitivity	Specificity
4	0.8551	0.8409	0.8732

Table 2

IV. CONCLUSION AND FUTURE WORK

In this work, we studied the possibility of the detection of sleep apnea events from the ECG signal variation patterns during sleep. We further developed a model using the ECG signal features. From the experimental results, we conclude that SVM with linear kernel shows the best accuracy with 15 second epoch length.

As a future work, we plan to do performance optimization for feature selection, and then incorporate this work into a real- time monitoring system that acquires and analyzes the ECG signal of subjects during sleep.

ACKNOWLEDGMENT

The authors would savor to consecrate R. Horváth, an old school in respiratory medicine mutually the Sleep Laboratoryof the National Korányi Institute, Budapest, Hungary, for the uphold provided for this study.

REFERENCES

[1] B.L.Koley, D.Dey, "Real time adaptive apnea and hypoapnea event detection methodology for portable sleep apnea monitoring device", IEEE Trans. Biomedical engg, dec.2013.

[2] A. Garde, W. Karlen, P. Dehkordi, D. Wensley, J. M. Ansermino, "Oxygen Saturation in Children with and without Obstructive Sleep Apnea Using the Phone-Oximeter" in 35th Ann. Int. IEEE EMBS Conf., Jul.2013.

[3] M. Bsoul, H.Minn, L.Tamil," Apnea MedAssist: Real-time Sleep Apnea Monitor Using Single-Lead ECG," " IEEE Trans. Inf. Technol. Biomed., May 2011.

[4] B. Xie, and H. Minn, "Real Time Sleep Apnea Detection by Classifier Combination," in IEEE Transactions on Information Technology in Biomedicine, vol.16, no. 3, pp. 469-477, May. 2012.

[5] PhysioNet, *www.physionet.org*.

[6] Goldshtein, A. Tarasiuk and Y. Zigel, "Automatic Detection of Obstructive Sleep Apnea Using Speech Signals," in IEEE Transactions on Biomedical Engineering, vol. 58, no. 5, pp. 1373- 1382, May. 2011.

[7] D. Alvarez, R. Hornero, D. Abasolo, F. Campo and C. Zamarron, "Nonlinear Characteristics of Blood Oxygen Saturation from Nocturnal Oximetry for Obstructive Sleep Apnoea Detection," Institute of Physics Publishing, vol. 27, no. 4, pp. 399-412, Apr. 2006.

[8] D. Avarez, R. Hornero, J. Marcos, F. Campo and M. Lopez, "Spectral Analysis of Electroencephalogram and Oximetric Signals in Obstructive Sleep Apnea Diagnosis," in Proceedings of the 31st IEEE International Conference on Engineering in Medicine and Biology Society (EMBS 2009)