Classification of Obstructive and Central Sleep Apnea Using Wavelet Packet Analysis of ECG Signals

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Abstract

Obstructive sleep apnea (OSA) causes a pause in airflow with continuing breathing effort. In contrast, central sleep apnea (CSA) event is not accompanied with breathing effort. The aim of this study is to differentiate characteristics of CSA and OSA using wavelet packet analysis of ECG signal over 5 second period and support vector machines. Six patients were used in the study that contained both CSA and OSA events. Eight level wavelet packet analysis was performed on each 5 sec clip using Daubechies (DB3) mother wavelet. Two features namely the best tree and the entropy of the best wavelet tree were extracted from each clip. One patient was used for testing at a time while all other patients' data was used for training. The accuracy range was between 82% and 92% with best tree as features. Entropy of best tree resulted in improved accuracies ranging between 87% and 94.5%.

1. Introduction

Healthy sleep is an essential mechanism for maintaining mental as well as physical health. Temporary seizure of respiration during sleep is referred to as sleep apnea. Sleep apnea can be broadly classified into hypopnea caused due reduction in airflow, obstructive sleep apnea (OSA) caused due to upper airway collapse and central sleep apnea (CSA) caused due to lack of neural input from the central nervous system [1]. If the rate of apnea is greater than five per hour it is usually referred to as sleep apnea syndrome and has to be clinically evaluated and treated [1].

There are many methods to diagnose sleep apnea. Polysomnography is a standard method for sleep apnea diagnosis where the patient has to spend the whole night in a sleep lab. Several parameters such as nasal pressure, abdominal effort, thoracic effort, EEG and ECG are collected and manually scored by an expert. There has been lot of effort of late to automate this scoring specifically using ECG alone. The effort in this work is to find characteristic difference in ECG between central sleep apnea and obstructive sleep apnea which occur in the same patient. In some sense, the focus of this work is to characterize the pathogenesis of OSA and CSA [2] using time frequency analysis. Recently, Thomas *et al.* [3] have reported moderate accuracies to differentiate OSA and CSA but their work has been very exhaustive. They use spectrograms to differentiate between subjects with OSA and CSA. In this paper, wavelet packet analysis with support vector machines is used to address the same issue using short term ECG signal. Six patients are chosen for this study who showed both CSA and OSA during the polysomnographic studies. Our earlier work using discrete wavelet transform and neural networks has been improved to differentiate between OSA and CSA [4].

2. Methods

Classification of apnea into obstructive and central sleep apnea is one of the most challenging stages in automatic detection and labeling of apnea specifically when ECG is used for classification. This is because of the fact that there is a high degree overlap in characteristics of the ECG signal between OSA and CSA. We use wavelet packet analysis to represent the ECG signal for classifying between CSA and OSA. In this section the proposed methodology using wavelet packet analysis and support vector machines is presented.

In total, 6 overnight sleep studies were used to develop our classification algorithms and provide an independent test performance assessment of our model. Sleep studies were collected from the database of Institute of sleep and breathing, Austin Hospital, Melbourne, Australia. The polysomnograms of 6 sleep apnoea patients who showed both OSA and CSA in the manually segmented recordings. All subjects were free of any cardiac history. The number of CSA and OSA epochs of the six patients analyzed is summarized in table 1.

2.1. Wavelet packet analysis

Wavelets [5, 6] are mathematical functions that decompose the data into different frequency components and study each component with a resolution matched to its

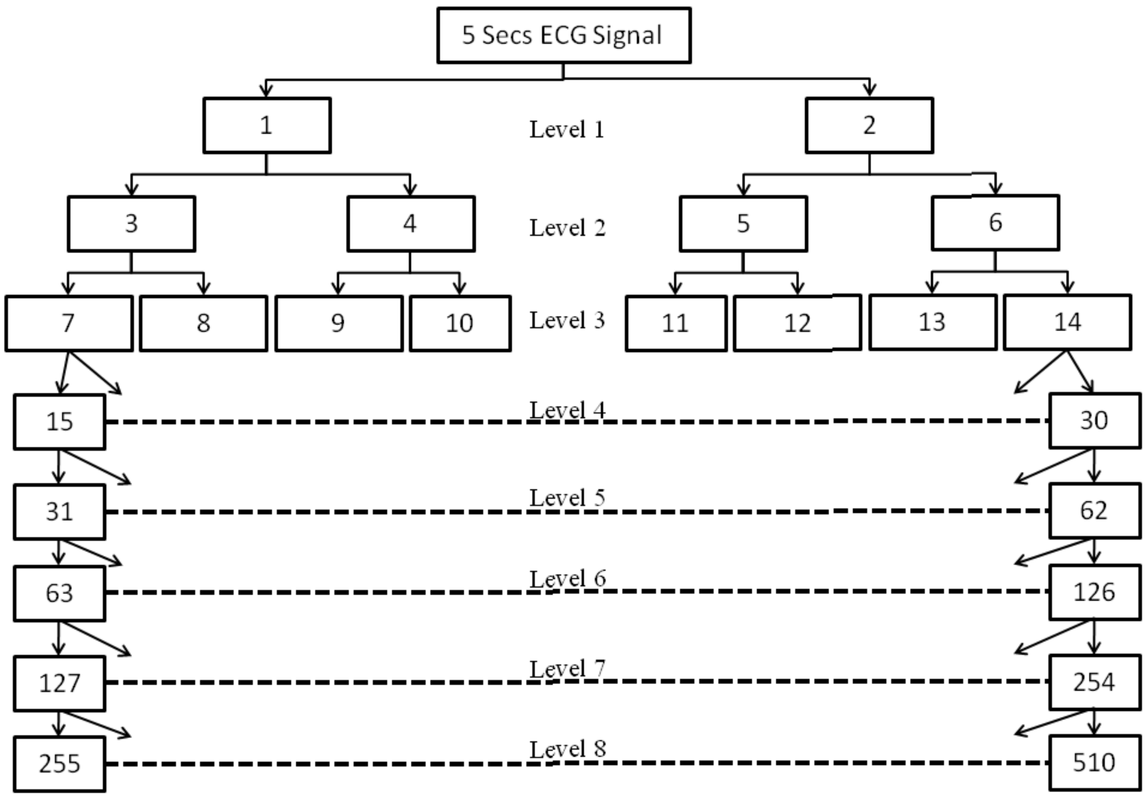

Figure 1. Illustration of 8 level Wavelet Packet Analysis and the Corresponding Bin numbers used in this work

Table 1. Number of five second CSA and OSA epochs in different patient datasets used in analysis

Patient ID	Number of CSA epochs	Number of OSA epochs
38	535	1551
51	104	1204
53	135	5167
61	349	7934
62	135	5167
70	349	7934

scale. This is a fast, linear, invertible orthogonal transform with the basic idea of defining a time-scale representation of a signal by decomposing it onto a set of basis functions, called wavelets. They are suitable for the analysis of non-stationary signals since it allows simultaneous localization in time and scale.

The continuous wavelet transform (CWT) of a function f using a wavelet function basis is defined by Equation 1.

$$f(a,b) = \frac{1}{\sqrt{a}} \int f(t)\Psi^{*}(\frac{t-b}{a})dt \tag{1}$$

where $\Psi(t)$ is called the mother wavelet function, a is the scaling (compression or dilation) coefficient, b is the translating (shifting) coefficient and $\frac{1}{\sqrt{a}}$ is a normalizing factor which is applied to make the transformed signal have the same energy at every levels. All the wavelet functions used in the transformation are derived from the mother wavelet through translation (shifting) and scaling (dilation or compression).

There are a number of basis functions that can be used as the mother wavelet. Since the mother wavelet produces all wavelet functions used in the transformation through translation and scaling, it determines the characteristics of the resulting wavelet transform. Depending on the application the appropriate mother wavelet has to be chosen for efficient working of the wavelet transform. Daubechies third order moments (db3) has been chosen as mother wavelets for feature extraction in our analysis.

The regular wavelet decomposition method described above may not yield the best result always. Hence a more exhaustive decomposition as shown in figure 1 can be used [7]. This is referred to as wavelet packet analysis. In this method, the signal is initially decomposed into two subbands at level 1 (denoted by bins 1 and 2 in figure 1). If the maximum frequency contained in the signal is 64 Hz, bin 1 represents frequencies from 0 to 32 Hz and bin 2 represents frequencies between 32 and 64. Further decomposition at level 2 would result in bins 3, 4, 5 and 6 with frequency range between 0-16, 16-32, 48-64 and 32-48. We perform decompositions up to level 8 which results in 510 bins. However, as only the best tree was being used, approximately 25 features per clip was used in classification. Once the signal is decomposed, best tree based on Shannon's criterion is calculated. If the bin is a part of the best tree, then we use one to represent this zero otherwise. This will result in a sparse matrix as only 25 bins on an average form a part of the best tree. To achieve better result, we also calculate entropy of the best tree and use them in second set of experiments.

2.2. Support vector machines

Support Vector Machines introduced by Vapnik [8] are a relatively new class of learning machines that have evolved from the concepts of structural risk minimization (SRM) [9] and regularization theory. They are also known as maximum margin classifiers as they simultaneously minimize the empirical classification error and maximize the geometric margin. A SVM performs classification by constructing an N-dimensional hyperplane that optimally separates the data into two categories.

By combining max-margin classification and empirical risk minimization, using structural risk minimization, and also applying the kernel trick to achieve nonlinearity, support vector machines are able to tackle highly complex classification tasks and generalize well without suffering from over-fitting or the so-called "curse of dimensionality". They are also mathematically tractable and have a unique global solution, both of which are highly desirable traits. The basic idea of SVM theory is to (implicitly) map the training data into higher dimensional feature space. A hyperplane (decision surface) is then constructed in this feature space that bisects the two categories and maximizes the margin of separation between itself and those points lying nearest to it (the support vectors). This decision surface can then be used as a basis for classifying vectors of unknown classification.

The SVM Light [10] implementation for support vector machines was used in all the experiments. The radial basis function (RBF) kernel given in Equation 2 is used for testing the features.

$$K(x,y) = exp\left(\frac{-\|x-y\|^2}{\gamma}\right) \quad (2)$$

Both the sets of features were used separately for classification using the support vector machines. Radial basis kernel with parameters C = 100 and gamma of 0.1 was chosen for final testing after parameter grid analysis. Leave one patient out error was calculated.

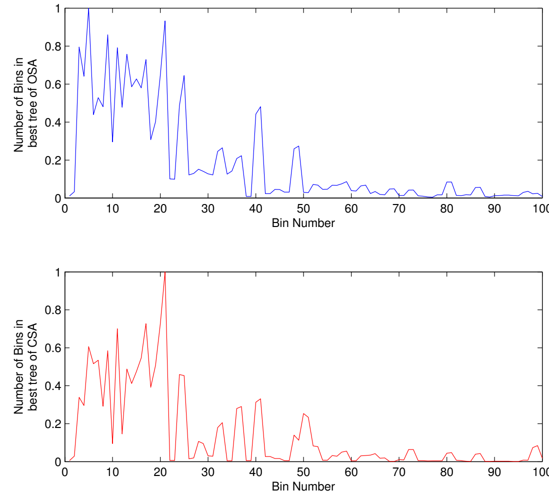

Figure 2. Histogram of bin coverage by best trees of all OSA and CSA epochs

3. Results

To understand the frequency distribution of ECG signal during OSA and CSA, best tree and entropy of the best tree were used. By closely analyzing the packets, OSA best tree was predominantly found in the left hand side of the figure 1 indicating the role of low frequency component. However, CSA best trees were predominantly on the middle and right side of the figure 1. To show that the bins occupied by the two cases were almost mutually exclusive, we plot the histogram of the first 100 wavelet packet bins as shown in figure 2. As it can be clearly seen, the bin occupancy is quite different for both the cases. This was the motivation behind trying a non-linear classifier such as support vector machines.

In the second part of the experiments, support vector machines were used to classify the WPA features extracted. The results of the best tree features and the entropy of the best tree features are shown in table 2. As it can be seen, the accuracy of best tree analysis range from 81.87% to 91.74%. In comparison, entropy of best tree as features resulted in accuracies ranging from 86.93% for patient 51 to 94.51% for patient 53. The sensitivities and specificities for both analysis are higher than 0.8 which indicates that the model is neither over-fit nor under-fit. Another important point to note is the specificity values being higher for entropy of best tree compared to best tree features. This

Table 2. Results using Wavelet Packet Analysis

	Best Tree Analysis			Entropy of Best Tree Analysis		
Patient ID	Sensitivity	Specificity	Accuracy (%)	Sensitivity	Specificity	Accuracy (%)
38	0.88	0.85	85.95	0.94	0.90	90.80
51	0.96	0.91	91.74	0.94	0.86	86.93
53	0.83	0.82	81.87	0.92	0.95	94.51
61	0.86	0.87	86.93	0.92	0.88	88.41
62	0.90	0.86	85.87	0.90	0.94	94.00
70	0.92	0.83	83.56	0.89	0.91	90.69

indicates that there is a reduction in false alarms in five patients out of six when compared to the best tree analysis.

4. Conclusions

In this paper, a new algorithm using wavelet packet analysis as features and support vector machine as classifier is proposed for automatically classifying central sleep apnea (CSA) and obstructive sleep apnea (OSA). ECG signals over 5 second period is used in analysis. Six patients were used in the study that contained both CSA and OSA events. Two features namely the best tree and the entropy of the best wavelet tree were extracted from each clip after decomposing the signal into 8 levels using db3. Analysis of best tree for CSA and OSA events indicated that OSA is pre dominantly in the low frequency region. However, best tree of CSA clips was appearing on both high frequency and low frequency regions, specifically between 64 to 96 Hz. This was found to be the distinguishing feature between OSA and CSA. The combined result was 85.09% accuracy, 0.88 sensitivity and 0.84 specificity for best tree analysis. For entropy of best tree, accuracy of 91.16% was obtained with 0.92 sensitivity and 0.91 specificity. These results indicate the possibility of non-invasively classifying CSA and OSA events based on shorter segments of ECG signals.

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