Proceedings of the 2005 IEEE
Engineering in Medicine and Biology 27th Annual Conference
Shanghai, China, September 1-4, 2005

Detection of Arousals in Patients with Respiratory Sleep Disorders Using a Single Channel EEG

S. P. Cho[1], J. Lee[1], H. D. Park[1], K. J. Lee[1, 2]
[1]Department of Biomedical Engineering, College of Health Science, Yonsei University, South Korea
[2]Center for Emergency Medical Informatics, South Korea
E-mail: saylas@bme.yonsei.ac.kr

***Abstract*—Frequent arousals during sleep degrade the quality of sleep and result in sleep fragmentation. Visual inspection of physiological signals to detect the arousal events is inconvenient and time-consuming work. The purpose of this study was to develop an automatic algorithm to detect the arousal events. We proposed the automatic method to detect arousals based on time-frequency analysis and the support vector machine (SVM) classifier using a single channel sleep electroencephalogram (EEG). The performance of our method has been assessed using polysomnographic (PSG) recordings of nine patients with sleep apnea, snoring and excessive daytime sleepiness (EDS). By the proposed method, we could obtain sensitivity of 87.92% and specificity of 95.56% for the training sets, and sensitivity of 75.26% and specificity of 93.08% for the testing sets, respectively. We have shown that proposed method was effective for detecting the arousal events.**

Keywords—**Arousals, Sleep fragmentation, EEG, PSG, Time-frequency analysis, Support vector machine**

I. Introduction

Sleep in patients with a number of sleep disorders and in some elderly is punctuated with frequent, brief arousals defined as a temporary intrusion of wakefulness into sleep, or at least a sudden transient elevation of the vigilance level due to arousal stimuli or to spontaneous vigilance level oscillations [1][2].

Arousals during sleep may be induced by the stimulus from the various disorders. Arousal stimulus can be identified in some cases (e.g. apnea, leg movement, snoring). The important fact is that frequent arousals during sleep degrade the quality of sleep and result in sleep fragmentation. And it is clear that sleep fragmentation leads to increased daytime sleepiness [2]. Others reported that sleep fragmentation may also influence the impairment of cognitive function [3].

These arousals may be identified from a number of important physiological changes on the standard polysomnograms (PSG), which include increases in heart rate, blood pressure and electromyogram (EMG) activity and changes in electroencephalogram (EEG) activity [4]. Some definitions for arousal scoring have been published. The American Sleep Disorders Association (ASDA, now the American Academy of Sleep Medicine) 3-second rule is the most widely used definition [5].

According to the ASDA rules, arousals are transient events characterized by "an abrupt shift in EEG frequency, which may include theta, alpha and/or frequencies greater than 16Hz but not spindles" [2].

Generally, human expert inspect the PSG recording and mark the each arousal event. However, the visual inspection of the entire record to detect the arousal events is cumbersome and time-consuming work. In this respect the development of automatic or computerized method could decrease the time taken by experts and prompt the extensive application of arousal analysis.

In this paper, we proposed an automatic method to detect the arousal events using the features based on time-frequency representation from a single channel sleep EEG. We used support vector machine (SVM) in pattern classification. SVM is known that it has an advantage of offering a good performance of classification with even smaller learning data. The performance of our method was evaluated using PSG recordings of nine patients with respiratory sleep disorders.

II. Methodology

A. Subjects & Data Recordings

In this study, we used 9 PSG recordings from patients with sleep apnea, snoring and excessive daytime sleepiness (EDS) were used. The age ranged from 28 to 67 years (mean: 50.33). More information about the subjects is reported in Table 1.

Each subject underwent an overnight recording in sleep laboratory in Asan medical center (South Korea), where the data were collected by a digital PSG (Grass-Telefactor, USA).

TABLE I
Patient Information for Each Recording

Record #	Sex	Age(yr)	TST(min)	Arousal #	Diagnosis
1	M	50	359	251	Apnea, Snoring, EDS
2	M	28	381	100	Apnea, Snoring
3	M	61	314	122	Apnea, Snoring
4	M	48	285	181	Apnea, EDS
5	M	28	299	188	Apnea, Snoring
6	M	67	304	176	Apnea
7	M	60	434	184	Apnea
8	M	47	288	87	Apnea, Snoring, EDS
9	F	64	302	113	Apnea, Snoring, EDS

TST: total sleep time. EDS: excessive daytime sleepiness

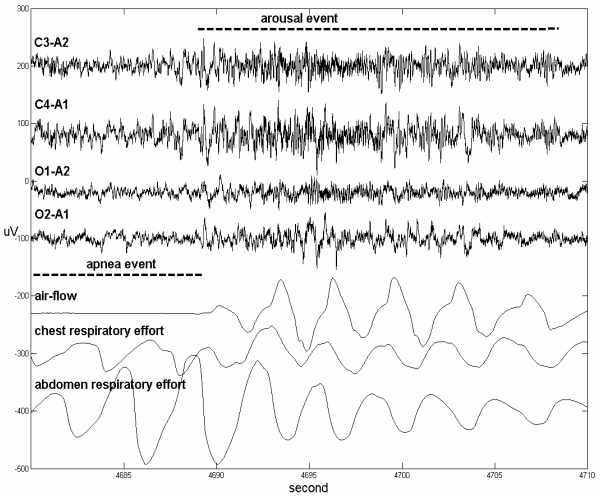

Fig. 1. Example of arousal in sleep stage 1.

The EEG (C4-A1, C3-A2, O2-A1, O1-A2) in accordance with 10-20 international system, left and right-electrooculargram (EOG), submental-EMG, air-flow, respiratory effort by piezoelectric band, pulse oximetry, electrocardiogram (ECG), and submental EMG were recorded. Each signal was recorded with a sampling rate of 200 samples/sec and 16-bit resolution.

B. Scoring of Events

All recordings were scored by a human expert in accordance with the conventional Rechtschaffen-Kales (R-K) rules for sleep staging and ASDA rules for arousal scoring, respectively. Then, we made second-by-second labels for arousal of each recording.

An example of arousal after the termination of apnea event in sleep stage 1 is presented in Fig. 1.

C. Data Analysis & Processing

In this study, the objective is to detect the arousals during sleep based on time-frequency with a single channel sleep EEG(C3-A2). According to the ASDA rules, arousal during REM sleep must be accompanied by an increase in submental EMG so that it was excluded in this study. And, it can be happened that an arousal can be scored in an epoch of recording which would be classified as wake by the sleep staging rule because arousal scoring is independent on sleep stages. So, the arousals during wake also excluded. Consequently, we have investigated the events occurred within sleep stage 1~4, that is, NREM sleep.

The frequency analysis of signal is usually performed by the Fourier transform. The Fourier transform of the signal identifies the frequencies present in the signal, but not the times when these frequencies occurred. That is, the Fourier transform can not show about the time information. In contrast, a time-frequency representation enables us to observe a density in time and frequency simultaneously that indicates which frequencies are present in the signal and how they change in time. The ability to simultaneously track time and frequency is very useful in analyzing complex physiologic signals [6]. In this paper, we used a spectrogram to estimate variations of frequency in time.

C1. Pre-processing & Time-Frequency Analysis

At the first, we implemented several stages of pre-processing to remove artifacts. We subtracted the mean value from the signal to make the zero-mean distribution and eliminated the portion of the signal that was above or below a specified range (-150 ~ +150uV) and band-pass filtered the signal from 0.5 to 50 Hz.

To estimate the changes of power spectrum in time, we computed the spectrogram with 257 points (1.285 seconds) Hanning window and the power spectrum was calculated every 60 seconds. The result of the time-frequency analysis was then used to evaluate the six frequency bands by adding the all values of each band: 0-0.5Hz (gamma), 0.5-4Hz (delta), 4-8Hz (theta), 8-12Hz (alpha), 12-16Hz (sigma), 16-30Hz (beta). Next, we computed the mean values of each band per one second and we applied the median filter to the mean values to get smooth signal.

C2. Feature Extraction

We selected the alpha and beta power as features according to the ASDA definition. Considering the changes of powers in time, we calculated the ratio between current alpha power and average alpha power during previous ten seconds. The ratio was also calculated for beta power as mentioned above. We also used average of ten seconds of alpha and beta power. We selected the ratio between sigma and alpha plus beta power, which could suggest the presence of sleep spindles [3]. Next, we computed the mean frequency of signal at every second and selected it as a feature. The selection of this feature was performed by heuristically. To know that the patient was in the sleep or wake state, we used the sleep stage information as another feature, which is scored by the expert. Consequently, we extracted these features at every second based on time-frequency analysis.

C3. Classifier & Post-processing

The purpose of support vector classification is to devise a computationally efficient way of learning good separating hyper-planes in a high dimensional feature space.

The SVM works in the high dimensional feature space formed by the nonlinear mapping, $\varphi(x)$ of the n-dimensional input vector into a K-dimensional feature space.

The equation of the hyper-plane separating two different classes is given by the relation

$$y(\mathbf{x}) = W^T \varphi(X) = \sum_{j=1}^{K} \omega_j \varphi_j(\mathbf{x}) + \omega_0 = 0 \qquad (1)$$

with $w=[\omega_0, \omega_1, ..., \omega_k]^T$ is the weight vector of the network.

By introducing the so-called Lagrange multipliers α_i, the learning task of SVM is reduced to quadratic programming. And all operations in learning and testing are done using so-called kernel functions. The kernel is defined as

$$\mathbf{K}(\mathbf{x},\mathbf{x}_i) = \varphi^T(\mathbf{x}_i)\varphi(\mathbf{x}) \quad (2)$$

In this paper, a radial basis function (RBF) was selected as kernel. SVM classifier parameters, kernel width σ and margin-losses trade-off C, affect the cost of learning and the classification performance. We have selected proper parameter values with experiments, in which the performance of classifier was observed for the different combination of parameters. We chose the parameters - kernel width σ and margin-losses trade-off C, which provided best classification, were fixed 1, 10, respectively, based on experiments.

In the last step we performed a post-processing to reduce some possibly incorrect detection. For example, event less than one second distant from a previous one was considered as a same event and we rejected the event less than three seconds.

III. Results & Discussion

We used three records (#1, #2, #3) as training sets and the other six records as testing sets. After the classification and post-processing procedure, true positive (TP), true negative (TN), false positive (FP) and false negative (FN) were classified. To assess the performance of the proposed method, we used two measures defined as equation (3), (4), respectively.

$$Sensitivity(\%) = \frac{TP}{TP + FN} \times 100 \quad (3)$$

$$Specificity(\%) = \frac{TN}{TN + FP} \times 100 \quad (4)$$

Table 2 shows the classification results of the training and testing sets. For training sets, the sensitivity was 87.92% while the specificity was 95.56%. Slightly lower results were obtained for the testing sets. The sensitivity was 75.26% while the specificity was 93.08%.

Some errors were caused by the difference between the duration scored by expert and that of the proposed method. Also, artifacts, e.g. motion artifacts, caused the errors.

However, the proposed method showed good performance, even though we have used only a single channel EEG.

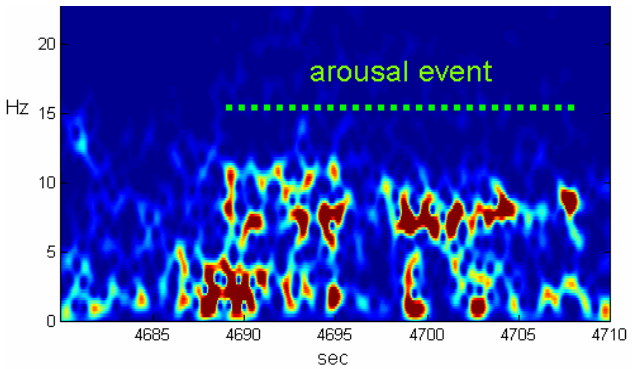

Fig. 2. Example of the spectrogram of the EEG at arousal in Fig. 1

TABLE II
The Overall Sensitivities and Specificities for The Training Sets and Testing Sets

Record #	Sen. (%)	Spec. (%)
1	87.20	94.31
2	88.44	95.75
3	88.13	96.59
Average (training set)	**87.92**	**95.56**
4	84.88	93.25
5	84.12	94.73
6	78.48	92.05
7	66.39	93.96
8	77.77	92.60
9	59.91	91.88
Average (testing set)	**75.26**	**93.08**

VI. Conclusion

In this paper, we proposed the automatic method to detect arousals that is based on time-frequency analysis and the SVM classifier using a single channel EEG. The performance of our method has been assessed using PSG recordings of nine patients with sleep apnea, snoring and EDS. By the proposed method, we could obtain sensitivity of 87.92%, and specificity of 95.56% for the training sets, and sensitivity of 75.26% and specificity of 93.08% for the testing sets, respectively. Although we have investigated events occurring in sleep stage 1~4, we have shown that the features based on time-frequency analysis from a single channel EEG and SVM classifier are effective for detecting the arousal events without other signals.

Acknowledgment

This study was supported by a grant of the Korea Health 21 R & D Project, Ministry of Health and Welfare, Republic of Korea. (02-PJ3-PG6-EV08-0001)

References

[1] P. Halasz, M. Terzano, L. Parrino, R. Bodizs, "The nature of arousal in sleep," J. Sleep Res., vol. 13, pp. 1-23, 2004.
[2] ASDA Report, "EEG Arousals: scoring rules and examples," Sleep, vol. 15(2), pp. 173-184, 1992.
[3] F. D. Carli, L. Nobili, P. Gelcich, F. Ferrillo, "A method for the automatic detection of arousals during sleep," Sleep, vol. 22(5), pp. 561-572, 1999.
[4] M. J. Drinnan et al., "Automated recognition of EEG changes accompanying arousal in respiratory sleep disorders," Sleep, vol. 19(4), pp. 296-303, 1996.
[5] R. J. Thomas, "Arousals in sleep-disordered breathing: patterns and implications," Sleep, vol. 26(8), pp. 1042-1047, 2003.
[6] G. D. Baura, System theory and practical applications of biomedical signals, Wiley-IEEE press, 2002, pp. 87-111.