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EEG Characteristic Analysis of Sleep Spindle and K-Complex in Obstructive Sleep Apnea

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Abstract This Paper Describes a Method for the Evaluation of Sleep Apnea, Namely, the Peak Signal-to-noise ratio (PSNR) of Wavelet Transformed Electroencephalography (EEG) Data. The Purpose of this Study was to Investigate EEG Properties with Regard to Differences between Sleep Spindles and K-complexes and to Characterize Obstructive Sleep Apnea According to Sleep Stage.We Examined Non-REM and REM Sleep in 20 Patients with OSA and Established a New Approach for Detecting Sleep Apnea Base on EEG Frequency Changes According to Sleep Stage During Sleep Apnea Events.For Frequency Bands Corresponding to A3 Decomposition with a Sampling Applied to the KC and the Sleep Spindle Signal. In this Paper, the KC and Sleep Spindle are Ccalculated using MSE and PSNR for 4 Types of Mother Wavelets. Wavelet Transform Coefficients Were Obtained Around Sleep Spindles in Order to Identify the Frequency Information that Changed During Obstructive Sleep Apnea. We also Investigated Whether Quantification Analysis of EEG During Sleep Apnea is Valuable for Analyzing Sleep Spindles and The K-complexes in Patients. First, Decomposition of the EEG Signal from Feature Data was Carried out using 4 Different Types of Wavelets, Namely, Daubechies 3, Symlet 4, Biorthogonal 2.8, and Coiflet 3. We Compared the PSNR Accuracy for Each Wavelet Function and Found that Mother Wavelets Daubechies 3 and Biorthogonal 2.8 Surpassed the other Wavelet Functions in Performance. We have Attempted to Improve the Computing Efficiency as it Selects the most Suitable Wavelet Function that can be used for Sleep Spindle, K-complex Signal Processing Efficiently and Accurate Decision with Lesser Computational Time.

Key Words : EEG(electroencephalography), OCA(obstructive sleep apnea), WT(wavelet transform), Sleep Spindle, K-complex

1. Introduction

Obstructive sleep apnea (OSA) [1-2]is the most common form of sleep-disordered breathing; specifically, it is defined by respiratory pauses with cessation of airflow lasting at least 10 s during sleep. OSA develops in approximately 2-5% of the adult population, making sleep apnea syndrome a widespread problem. Furthermore, patients with OSA have a significant risk for developing cardiovascular disease [3-4].

Sleep spindle and K-complexes constitute the physiological markers of sleep stage 2 non-rapid eye movement (NREM). Sleep

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spindles, first described in the human EEG by Loomis, Harvey, and Hobart (1935) [5], are transient waveforms around 12 - 14 Hz observed in cortical pyramidal neurons driven by thalamocortical oscillations that are active during sleep. K-complexes are sleep-specific, phasic EEG waveforms that may be spontaneous or elicited by stimulation. They have a duration of approximately 0.5 s and are characterized by a well-delineated negative component followed by a positive deflection (Rechtschaffen and Kales, 1968) [6]. Amzica and Steriade have recently shown that K-complexes result from a synchronized cortical network that imposes periodic excitatory and inhibitory actions on cortical neurons, thus creating cortically generated slow oscillations (0.5 - 0.9 and 1 - 4 Hz), which spread through the cortex and are transferred to the thalamus.

The EEG signal is considered non-stationary as its properties change during each sleep apnea. Therefore, classical spectral methods are not appropriate for feature extraction, since they provide a description of the frequency contents of the EEG signal, but not the timing of the signal. Timing information is required for EEG signal analysis since parts of an EEG wave may exist in part of the epoch but not in the entire epoch.

Manual scoring of these two morphologically distinct wave- forms which are hallmarks of Stage 2 sleep is time consuming and risks being subjectively interpreted. Thus automatic identification of these modalities would be beneficial [7]. These approaches range from period-amplitude analysis [8-9], spectral analysis through Fourier transform [10], wavelets [11-12].Paper comparison of the performance obtained by different techniques is difficult because dissimilar performance measures are used, results are highly dependent on the manual scorers whose scoring serves as ground truth and different measures are taken to reduce the problems related to different expert based scoring

The several soft-computing methods have been proposed in the literature for the diagnosis of the sleep spindle, K-complex [13]. They include template matching [14], time domain, frequency domain [15] and time - frequency domain [16] which are very few. There is no standard method for selecting the best wavelet for processing EEG signals [17-19].

The present study also compared the peak signal-to-noise ratio (PSNR) with the K-complex and sleep spindle patterns of sleep apnea signals that could be resolved by using various types of mother wavelets on the analysis of power quality signals. We can be used for sleep spindle, K-complex signal processing efficiently and decision accurately with lesser computational time.

2. Materials and Methods

2.1. Subjects and database preparation

We included 20 patients with OSA in this study. The mean age of patients with OSA was 53.40 ± 3.92 years. Subjects underwent a physical examination and a neurological evaluation, including medical, psychiatric and sleep history. Experiments were conducted at the Keimyung University Dongsan Hospital's Department of Neurology in Daegu. The EEG was recorded using a digital recording system (Grass Technologies) with EEG filters set at 1 and 70 Hz. PSG recording was performed using 4 EEG leads at the C3-A2, C4-A1, O1-A2, and O2-A1 channel positions. Impedance for the EEG electrodes was kept

below 5 kΩ. Activity was captured continuously overnight by a personal computer (Twin model polygraph) through an analog-to-digital converter with 12-bit resolution and a sampling rate of 200 Hz for off-line analysis using the acquisition program. We investigated the ability to discriminate detection and classification and attempted to characterize different behaviors of sleep spindle and K-complex during sleep apnea according to sleep stage. Data analysis was performed on EEG signals during the following sleep stages: 1 - 2 (light sleep), 3 (deep sleep), and rapid eye movement (REM) sleep. Total OSA recording time for each subject was approximately 7 h. OSA data for each subject included data from the four EEG channels (O1-A2, O2-A1, C1-A2, and C2-A1) used to determine the threshold values of EEG spindle detection. EEG electrodes were placed according to the international 10-20 system of electrode placement [20-22].

The apnea hypopnea index (AHI) and respiratory disturbance index (RDI) are often used as equivalent terms. However, in some sleep centers, the RDI = AHI + RERA (respiratory effort-related spindle) index; RERAs are sleep spindles associated with respiratory events not meeting the criteria for apnea, and the RERA index is the number of RERAs per hour of sleep. One can use the AHI to grade the severity of sleep apnea. Standard levels include normal (AHI $<$ 5/h), mild (5 $\leq$ AHI $\leq$ 15/h), moderate (15 $<$ AHI $\leq$ 30/h), and severe (AHI $>$ 30/h). Our patients included 10 with severe AHI (37.27 ± 6.3), 5 with moderate AHI (20.87 ± 4.2), and 5 with mild AHI (8.4 ± 3.3).

2.2. Sleep spindle and the K-complex in PSG records

Sleep spindles were scored visually on the 4 EEG channels during sleep stage 2 for the entire night. In addition, the EEG recording was analyzed for the presence of sleep spindles and K-complexes. The only modification made was a shorter interval (1.5 s instead of 3 s) of EEG changes; this change was made to allow for an increased time resolution of the analysis. To qualify as a sleep spindle, EEG events had to show a predominant frequency between 12 and 14 Hz, and had to stand out clearly from background activity. The amplitude and duration of waveforms change abruptly for each frequency component, and a rapid increase in central frequency occurs. Although the magnitudes of spindle responses differ for different responses of the same subject and responses of different subjects, the detection of EEG spindles related to pathological events is important, particularly for OSA.

The K-complex is a complex multi functional phenomenon of the sleeping brain that is involved in information processing and defense against the normal spindle effects of sensory stimuli. K-complexes are an important component of EEG transients associated with respiratory event termination in our experimental data. Transients can appear spontaneously or may be triggered by various stimuli, and could represent signs of spindle or a sleep protective (defensive) function. A K-complex is an EEG waveform that occurs during stage 2 of non-REM sleep. It is the most prominent event in the EEG of a healthy human. The presence of the K-complex in stage 2 creates a slow wave ($<$1 Hz) signal caused by the oscillation of cortical neurons; this can be followed by a sleep spindle. Each appearance of apnea results in reduced amplitude of the airflow signal relative to the normal amplitude. Examples of the time domain results of the EEG K-complex response, sleep spindle, and

nasal pressure during sleep stage 1 - 2 are shown in Figure 1.

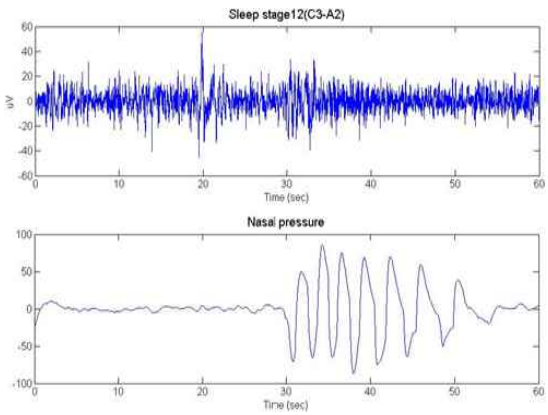


Fig. 1 Time domain analysis of K-complex (pre-arousal) and sleep spindles according to apnea events and nasal pressure

2.3. Wavelet transformation

Wavelet analysis is a powerful method since it can be used to discriminate between non-stationary signals with different frequency features; by comparison, a Fourier transform can only be applied to stationary signals. Among the methods used for analyzing non-stationary signals such as EEG, wavelet analysis has been shown to be the most effective method in the frequency domain. Moreover, discrete WT analysis of EEG data is the most powerful tool for sleep spindle analysis in sleep apnea [23- 24]. The WT decomposes a signal into a basic function set called wavelet, thus providing sub-band localization. In the first step, the original signal is passed through a high-pass filter and a low-pass filter. After filtering, half of the samples at high frequency are eliminated according to Nyquist criteria. This process can be expressed by the following equations:

$$C_{high}[k] = \sum x[n].g[2k-1] \quad (1)$$

$$D_{low}[k] = \sum x[n].h[2k-n] \quad (2)$$

Where $C_{high}[k]$ and $D_{low}[k]$ are the high-pass (Di: detail) and low-pass (Ai: approximation) filters, respectively. A discrete wavelet transform(DWT) of sleep apnea EEGs was used to extract the features in the first set of experiments.

The regular WT gives a decomposition of a given signal into a set of Ai and Di coefficients of level i(i=1,...8)(shown as a frequency level in Table 2). The advantage of DWT over existing transforms, such as discrete Fourier transforms and DCT, is that the DWT enables multiresolution analysis of a signal with localization in both the time and frequency domain. The DWT calculates the wavelet coefficients at discrete intervals of time and scale instead of at all scales. Several sets of mother wavelets have been designed for WT analysis such as Daubechies, Symlet, Biorthogonal, and Coiflet, as shown in Figure 2.

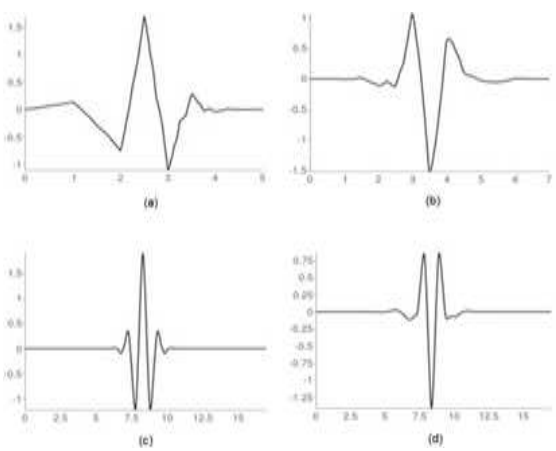


Fig. 2 Example of mother wavelet
(a) Daubechies 3, (b) Symlet 4,
(c) Biorthogonal 2.8, and (d) Coiflet 3

2.4. Preprocessing and performance parameters

The DWT has been applied to the vibration signals obtained with different mother wavelets: ranging from different types of Daubechies (1 to 9), Symlet (2 to 8), Biorthogonals (1.1, 1.3, 1.5, 2.2, 2.4, 2.6, 2.8, 3.1, 3.3, 3.5, 3.7, 3.9, 4.4, 5.5, 6, 8), and Coiflet (1 to 5).The Daubechies wavelet filters can be readily computed via spectral factorization of a symmetric positive polynomial [25]. Significant advantages of the spectral factorization approach include its generalizability to many different classes and families of wavelets, its suitability for easily interpretable visual displays, and thus its practicality in pedagogy. We used 4 wavelet-type functions in these experiments. WT decomposes a given signal into a set of approximation and detail coefficients by levels. The decomposition process can be iterated with successive approximations being decomposed, in turn, so that a signal is broken down into several lower-resolution components. For sleep apnea events, the K-complex and sleep spindle are processed to obtain a level A3 (0 - 12.5 Hz) transformation.

Different types of mother wavelets can be used to obtain this decomposition. For the multiresolution decomposition process, selection of the appropriate mother wavelet and the number of decompositions is made based on the dominant frequency components of the signal. For this study, the absolute value of the approximation coefficient (A3) was the set of inputs that yielded the best K-complex and sleep spindle pattern results. The number of coefficients supplied by the WT depends on the number of samples of the chosen patterns. For frequency bands corresponding to A3 decomposition with a sampling frequency of 200 Hz, mother wavelets of Daubechies (Db), Symlets (Sym), Biorthogonal (Bior), and Coiflet (Coif) were applied to the K-complex and the sleep spindle signal.

The analysis of the EEG signal depends on the localization of the different EEG wavelets in both time and frequency. For this reason, features were extracted using entropy estimation at different scales (frequency band). The entropy is defined as:

$$E = -\sum_{i=1}^{n} p_i \log p_i \tag{3}$$

where p_i is the probability mass function of the wavelet coefficients in the band of interest represented by their histogram with n.

In this paper, the K-complex and sleep spindle are calculated using mean square error (MSE) and PSNR for 4 types of mother wavelets. MSE is one of many metrics used to quantify the difference between values implied by an estimator and the true values of the quantity being estimated.

$$MSE = \frac{1}{n}\sum_{k=0}^{n-1}[x(k) - y(k)]^2 \tag{4}$$

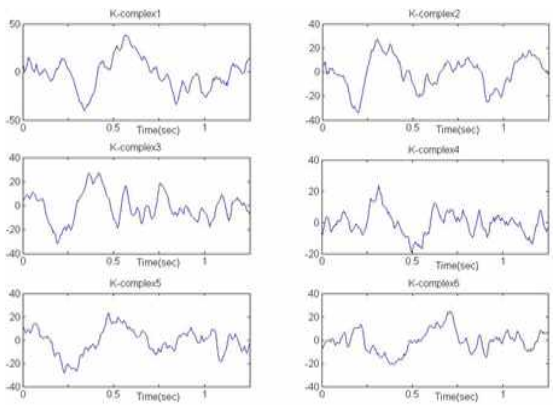
PSNR is the ratio between the maximum possible power of a signal and the power of the error (noise) affecting the fidelity of its representation.

$$PSNR = 10\log_{10}\left(\frac{MAX_1^2}{MSE}\right) \tag{5}$$

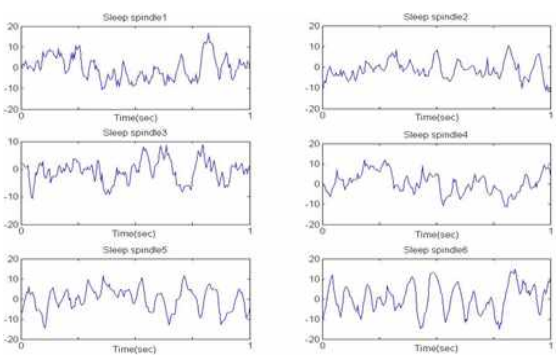
MAX_1^2 is the maximum possible value of the signal.

3. Results

We propose a method for predicting apnea-related arousal events during sleep apnea episodes in adults. Sleep EEG data are classified into 3 groups according to pathological significance: sleep stages 1-2, 3, and REM. In this study, we quantitatively measured the relationship between the K-complex and sleep spindle during sleep apnea in PSG recordings. Sleep apnea signals are of primary interest because of their association with respiratory disorders, and apnea events can be directly detected using these signals. K-complex and sleep spindle event signals during sleep stage 1-2 in the time domain are shown in Figure 3. Figure 4 illustrates the relationship between frequency and scale. To illustrate the idea of using multiple wavelets for time-frequency entropy, consider the signal shown in Figure 5. The signal was obtained at a sampling rate of 200 Hz, and the CWT using the mother wavelet gaus 4 was calculated and is shown in Figures 5a-c. This method was devised during maximum frequency and CWT analysis for examining the characteristics of non-REM and REM sleep stages. We showed that this could be easily divided with the maximum energy in the scalogram.



(a) K-complexes



(b) Sleep spindles

Fig. 3 EEG signals showing K-complex and sleep spindle events during sleep apnea

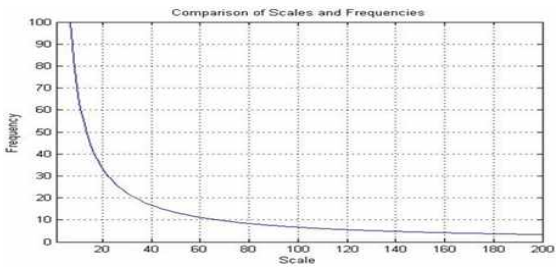
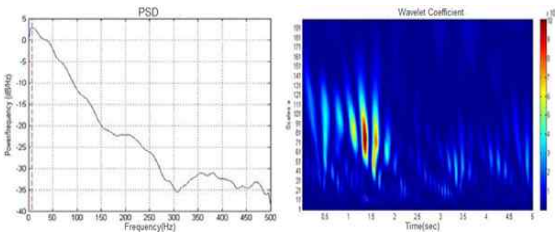


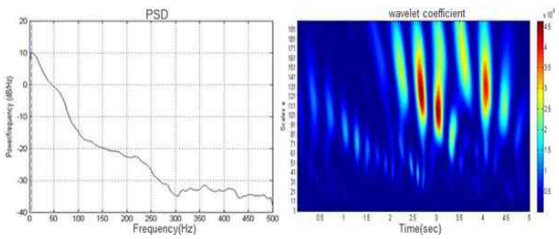
Fig. 4 EEG signal showing a proportional relationship between frequency and scale level during sleep

Fig 5. (a)-(c) and Table 1 show that the characteristics of the frequency of sleep stages were different. During sleep stages 1 - 2, 3, and REM, the average frequencies were 6.67 Hz, 5.34 Hz, and 6.72 Hz, respectively. Next, power variability was calculated level by level as coefficient variances.

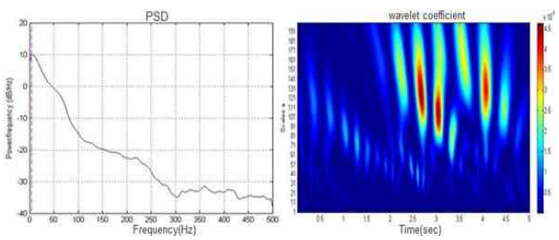
The relationships between the K-complex, sleep spindle, and sleep apnea are explored in Table 2. The frequency bands of each approximation that was decomposed using WT are shown in Table 2. Usefulness of Db3, Sym4, Bior2.8, and Coif3 were assessed, and comparative mother wavelet types are displayed. The K-complex and sleep spindle patterns obtained using each wavelet function as an input feature are shown in Table 3 and are reported in terms of the PNSR. We compared the PSNR accuracy for each wavelet function and found that mother wavelets Db3



(a)



(b)



(c)

Fig. 5 Comparison of power for frequency and scale levels according to the sleep stage: (a) stage 1 - 2, (b) stage 3, and (c) REM

and Bior2.8 surpassed the other three wavelet functions in performance.

Therefore, mother wavelet Db3 found in K-complexes and Bior2.8 found in sleep spindles were selected for feature extraction. In patients with apnea, EEG frequency bands, including delta (0.5 - 3.5 Hz), theta (4 - 7.5 Hz), alpha (8 - 12.5 Hz), and beta (13 - 25 Hz), were measured according to sleep stage (Fig. 5a-c), and the amplitude of the powers in different frequency bands during the K-complex and sleep spindle events were obtained.

Figure 6 shown compared of the PSNR accuracy for each wavelet function and found

Table 1 Characteristics of frequency bands according to sleep stage

Sleep stage	Average Maximum Frequency(Hz)	Scale levels (Maximum energy density)
Sleep stage1-2	6.67±1.55	90±12.11
Sleep stage3	4.34±1.22	125±17.77
REM	6.72±2.22	81±4.77

Table 2 Frequencies corresponding to different levels of decomposition for Db3 order 8 wavelet with a sampling frequency of 200 Hz

Level	Approximation(A) Frequency range(Hz)	Detail(D) Frequency range(Hz)
1	0-50	50-100
2	0-25	25-50
3	0-12.5	12.5-25
4	0-6.25	6.25-12.5
5	0-3.125	3.125-6.25
6	0-1.56125	1.56125-3.125
7	0-0.78125	0.78125-1.56125
8	0-0.3906	0.390625-0.78125

Table 3 Comparison of MSEs and PSNRs for the K-complex and sleep spindles obtained using 4 mother wavelets

Wave functions	MSE		PSNR(dB)	
	K-complex	Spindle	K-complex	Spindle
db3	11.66	20.040	27.39	25.04
Sym4	23.43	16.862	24.36	25.79
Bior2.8	15.15	4.125	26.25	31.39
Coif3	13.23	19.252	26.85	25.22

that mother wavelets Daubechies 3 and Biorthogonal 2.8 surpassed the other wavelet functions in performance. By measuring the EEG amplitude in the different frequency bands, we obtained the plots shown in Fig 7(a-c) by using 5-s EEG signal spindle events during apnea episodes. These spindle (5-s EEG) segments were formed by going forward at 15 s. Sleep stages 1 - 2, 3, and REM were

primarily included with alpha and theta band frequencies.

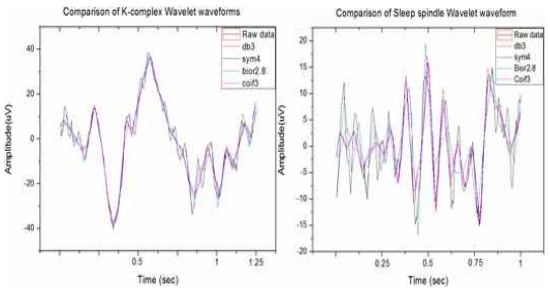
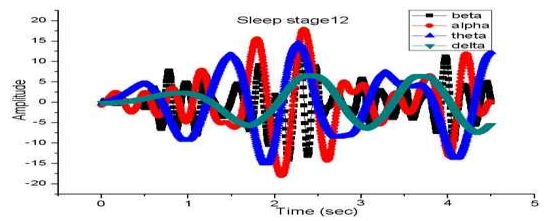
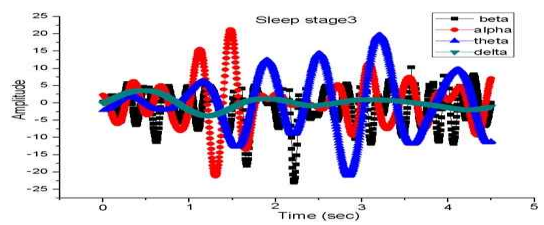


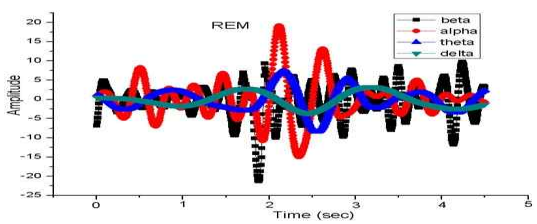
Fig. 6 Comparison of patterns for K-complex and sleep spindle signals obtained using 4 wavelet methods



(a)



(b)



(c)

Fig 7.Comparison of power of frequency bands for sleep spindle events during sleep: (a) stage 1 - 2, (b) stage 3, and (c) REM

4. Discussion and conclusions

The main purpose of this study was to develop an efficient signal preprocessing method to examine frequency characteristics of K-complex events and sleep spindle EEG with higher detection accuracy. To achieve this goal, we examined non-REM and REM sleep in 20 patients with OSA and established a new approach for detecting sleep apnea based on EEG frequency changes according to sleep stage during sleep apnea events. Here, we demonstrate that these changes can be easily divided into frequency and scale levels of sleep spindle within each sleep stage by CWT. The EEG signals were decomposed into time-frequency components by using a WT, and features were calculated to depict their distribution. Simulation results showed that the Db3 and Bior2.8 mother wavelets increased pattern-matching efficiency better than some of the other common wavelets did.

Since the K-complex is part of the sleep spindle response, the transient intrusion of waking and the resultant transient depolarization of the thalamic nuclei should make it impossible for a spindle to be associated with these K-complexes. The role of K-complexes in sleep protection and deepening of sleep is supported by Amzica and Steriade's assumption [26]that their occurrence at a lower frequency than the other sleep rhythms and their wide synchronization at a cortical level cause their sharp onset. This sharp onset plays an important role by providing a synchronous input to thalamic neurons, triggering and grouping sequences of spindles or delta oscillations. The K-complex generally occurs during sleep stage 2 of non-REM sleep, but it can also occur after apneic episodes. Moreover, there is a general tendency for the K-complex to occur because of auditory stimuli. Although

it is difficult to establish an accurate definition because these events do not follow a regular pattern, the separation time between the K-complex and spindle was defined such that the event occurring 1 - 3 s before the sleep spindle was assumed to be the K-complex in this study. Our finding indicate that it is possible to predict the relationship between K-complex and snoring that resumes after an apnea episode, as well as the possibility that the K-complex can be triggered by the noise of rapid breathing or panting.

As the duration of apnea increases, the blood oxygen saturation (SaO2) naturally decreases, thereby requiring an increased breathing effort at the last stage of apnea to overcome this. Thus, the possibility of awakening during this process is also increased. In fact, people who have increasing apnea durations experience an extension of the hyperventilation process for compensation after apnea because of the complete loss of SaO2. For this reason, the possibility of an increase in the awakening duration can be predicted.

We expect that the results of this study will aid in identifying the mechanisms underlying the relationship between the K-complex and sleep spindle.

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