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Original Article

Assessment of Sleep Quality Based on Automatic Detection of Emotional Arousal Epochs from EEG Signal

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Abstract - *Nocturnal sleep is the main time to recover energy and repair cells in the human body. Hence, the detection of insomnia and the assessment of the quality of sleep are important in determining patients' states of health so that appropriate therapies can be administered. Many previous studies often evaluated sleep quality by analyzing positive and negative emotions; in this study, we developed a new method for evaluating the quality of sleep based on detecting the number of emotional arousal epochs during sleep. Emotional arousal epochs (each contains a 10-second segment of data) were extracted based on analyzing the standard epochs of emotional data. The densities of emotional arousal epochs were correlated with the states of the patient's health, and the results were compared to develop a table of relationships for the assessment of the quality of sleep. The densities of emotional arousal epochs were correlated with the states of the patient's health, and the results were compared to develop a table of relationships for the assessment of the quality of sleep. The new method has proven effective when integrated into an automatic identification system; this system identifies emotional segments and classifies sleep quality based on the intensity of emotional epochs in each sleep cycle with an average accuracy of 87.5%.*

Keywords - *Sleep, Emotional arousal, Wavelet entropy, Electroencephalogram, Sleep disorders.*

1. Introduction

Having a good quality of sleep is very important to everybody, but sleep disorders are a common occurrence. Those that occur most frequently are insomnia, narcolepsy, and sleep apnea. When a person has insomnia, negative emotions will likely occur at work the next day, such as hostility and fatigue [1]. Many other disorders manifest themselves through sleep disturbances. Sleep disturbances rank second-most popular among all illnesses worldwide. During sleep, the human brain and respiration go through several psychophysiological states, such as emotional feelings and arousal from sleep, which interfere with sound, stable sleep. Many approaches can be used to recognize disturbances in sleep or to classify the sleep stages. At present, the main diagnostic tools in sleep medicine are those that measure psychophysiological signals, such as polysomnography (PSG), which measures the effort expended in breathing; oxygen levels in the blood; electrical activity in the brain (EEG); electrocardiograms (ECGs); electrooculograms (EOGs); and muscle activity (EMG). Each method has its own strengths, but EEGs provide the most important signals in the field of sleep research. EEG signals can reveal unusual patterns that have sudden changes or abrupt shifts in frequency [2], and these signals provide mended scoring rules for the recognition of EEG patterns during sleep based on Rechtschaffen and Kales' (R&K's) manual that was developed in 1968 [3]. The frequency ranges of the EEG signal are segmented into some basic sub-bands, which are the delta band (0.5 - 4 Hz), the theta band (4 - 8 Hz), the alpha band (8 - 12 Hz), and the beta band (>12 Hz).

1.1. An Overview of Sleep Stages

Sleep can be divided into two entirely different behavioral states: Rapid Eye Movement (REM) sleep and non-REM (NREM) sleep. Initially, during the awake stage, the EEG shows mixed beta and alpha activities as the eyes open and close, and when the eyes remain closed, alpha activity is predominant. The EMG reflects the high-amplitude muscle contractions and movement artifacts. The EOG shows eye blinking and rapid eye movement. The frequency and amplitude of the various events will diminish as the subject stops moving and becomes drowsy. After the subject falls asleep, he or she enters into what is known as NREM sleep, which consists of four stages. Stage 1 sleep is the period in which the subject drifts off, i.e., a transition period from wakefulness to the three stages of NREM sleep. This period has a short duration, usually lasting between one and seven minutes. Sleep stage 1 is characterized by low voltage with well-defined alpha and theta bands, mixed frequency EEG, as well as some slow, rolling eye movements and some relatively higher EMG activity. Stage 2 makes up the bulk of an average person's sleep each night, around 40% to 45%, and this stage can be recognized easily because of the presence of sleep spindles and K-complexes in the EEG waves. A sleep spindle is a rapid waxing and waning of the EEG waves in intervals of one to two seconds (about 12-14 Hz), while a K-complex is a large waxing and waning of a wave that somewhat resembles a mountain. Sleep stage 3 and sleep stage 4 are similar, and both fall into the category of slow-wave sleep (SWS) or deep sleep and they are so named because of the high amplitude delta waves in the EEG. Besides these four basic stages of sleep, a unique sleep stage exists, it's called REM sleep, which is a very active stage of sleep that comprises 15-25% of a normal night's sleep. During REM sleep, breathing, heart rate, and brain wave activity quicken, and vivid dreams can occur. Thus, this stage also is referred to as the dream stage [4].

1.2. Sleep Cycles

In nocturnal sleep, a cycle includes NREM and REM sleep, and the cycles initially vary in length from 80 to 100 minutes, and they may last from 90 to 120 minutes later in the night. There are about four to five cycles during a normal 8-hour sleep period, so REM sleep follows NREM sleep, and it occurs four to five times. The first period of REM sleep during the night may be less than 10 minutes in duration, while the last may exceed 60 minutes. In adults, stage 1 sleep usually accounts for 2-5% of the night's sleep, whereas stage 2 represents 45 to 65% of total sleep time. Stages 3 and 4 SWS occur mostly in the first third of the night, and they constitute 10 to 20% of total sleep time. REM represents 15 to 25% of total sleep time [5].

1.3. Emotional Arousal

Arousal is an abrupt change from sleep to wakefulness or from a "deeper" stage of non-REM sleep to a "lighter" stage. An EEG-arousal in sleep is defined as an abrupt shift in EEG frequency, lasting for three seconds or more, which may include theta, alpha, and/or frequencies greater than 16 Hz, but not spindles. There are two basic types of arousal: transient arousals, which are shorter than three seconds and normal arousals, which last from three to thirty seconds. Transient arousals are shorter than three seconds, so they are easily confused with K complexes and sleep spindles [6] because K-complexes usually occur close to the arousal changes from stage 2 to SWS.

Following Schachter and Singer's theories [7], the two-factor theory of emotion states that emotion is a function of both cognitive factors and physiological arousal. Physical arousal plays a primary role in emotions. However, this arousal is the same for a wide variety of emotions, so physical arousal alone cannot be responsible for emotional responses. During sleep, the energy of the theta or alpha waves (or both) surges instantaneously when emotional arousals appear, followed then by the increase of the beta wave. A person will typically feel groggier when he or she is awakened from SWS, and its effect is to make the subject seem to fall into the REM stage. However, it is not actually REM sleep, and it seems to resemble a psychedelic phenomenon. So, the number of emotional arousal epochs can influence the distribution of sleep stages in total sleep, and the intensity of emotional arousal relates to reduced amounts of sleep and increased nocturnal activity. From a healthcare perspective, the assessment of the patient's emotional state is essential in medical care. Thus, the assessments of epochs of emotional arousal can give us a fairly accurate view of the quality of a patient's sleep. In the past, many studies of the quality of sleep focused on insomnia states, sleep disorders [8], the recognition of arousal [9], and the relationships between the quality of sleep and emotions, including anxiety [10] and both positive and negative emotions [11,12,13]. However, previous studies have referred only to the parameters related to the quality of sleep in order to obtain specific results. This research considered the impact of the emotional arousal intensities on the quality of sleep and initially proposed a method of assessing sleep quality based on the three levels: I, II and III, corresponding to worst sleep, normal sleep, and good sleep, respectively. An automatic system is also proposed to classify sleep quality.

2. Method

2.1. Database

2.1.1. Sleep Data

EEG signals were recorded for 14 subjects (six males and eight females), whose ages ranged from 33-53 years old. The subjects did not use drugs or stay up late during the week of the tests. The sampling frequency was set to be 200 Hz. The NEC‖SYNAFIT1000 model was used to acquire the EEG brain waves. Data acquisition was performed using a general-purpose data acquisition unit (NI USB6210, National Instruments). Sleep states were surveyed by sleep experts based on questionnaires with questions for the assessments of "Difficulty falling asleep," "Had stresses during sleep," and "Often awake for a moment while sleeping." These questions could be rated 0-9, and the subjects were classified into three groups (worst sleep, normal sleep, and good sleep, which were expressed by the symbols I, II, and III, respectively). We classified the values of 7 - 9 as "very high", 4 - 6 as "high", 2 – 3 as "normal", and 0 – 1 as "low". The sleep states of the 14 subjects are listed in Table 1.

We developed the acquisition and processing software and the configuration of the acquisition system. The acquisition period lasted more than six hours. The sleep technician scored cycles of sleep stages according to R&K rules based on 10-second epochs of the single channel (C3-A1). The three sleep cycles that were obtained for each subject included information about all of the stages of sleep. The artifacts were removed manually by the group of sleep experts and the data are clean for researchers in this study.

Table 1. Sleep states of 14 subjects from the questionnaires

No	A	B	C	D	Groups
1	true	High	high	very high	I
2	true	very high	very high	very high	
3	true	High	high	very high	
4	true	High	very high	high	
5	true	normal	normal	high	II
6	false	normal	normal	high	
7	true	High	normal	high	
8	false	normal	normal	normal	
9	false	High	normal	normal	
10	false	*Low*	*low*	*low*	III
11	false	*Low*	*low*	*low*	
12	false	*Low*	*low*	*low*	
13	false	*Low*	*low*	*low*	
14	false	*Low*	*low*	*low*	
A: Patients think that they are having psychological problems B: The level of bad mood C: The level of stresses, D: The level of “awake a moment during sleeping.”					

2.1.2. Emotional Data

The emotion database from “Database for Emotion Analysis using Physiological Signals” (DEAP), available at http://www.eecs.qmul.ac.uk/mmv/datasets/deap/ was used in the assessment of the abrupt shift of EEG frequency and amplitude. The electroencephalogram (EEG) and peripheral physiological signals of 32 subjects were recorded as each subject watched one-minute-long excerpts from 40 music videos.

The subjects rated each video in terms of the levels of arousal, valence (scale ranges from unhappy or sad to happy or joyful), like/dislike, dominance, and familiarity. The sampling frequency of emotion data was 128 Hz. Frontal face videos also were recorded for 22 of the 32 subjects. A novel method for selecting stimuli was used, utilizing retrieval by affective tags from the last.fm website, ‘video highlight detection,’ and an online assessment tool. Only emotion data with low values of arousal were used in our tasks.

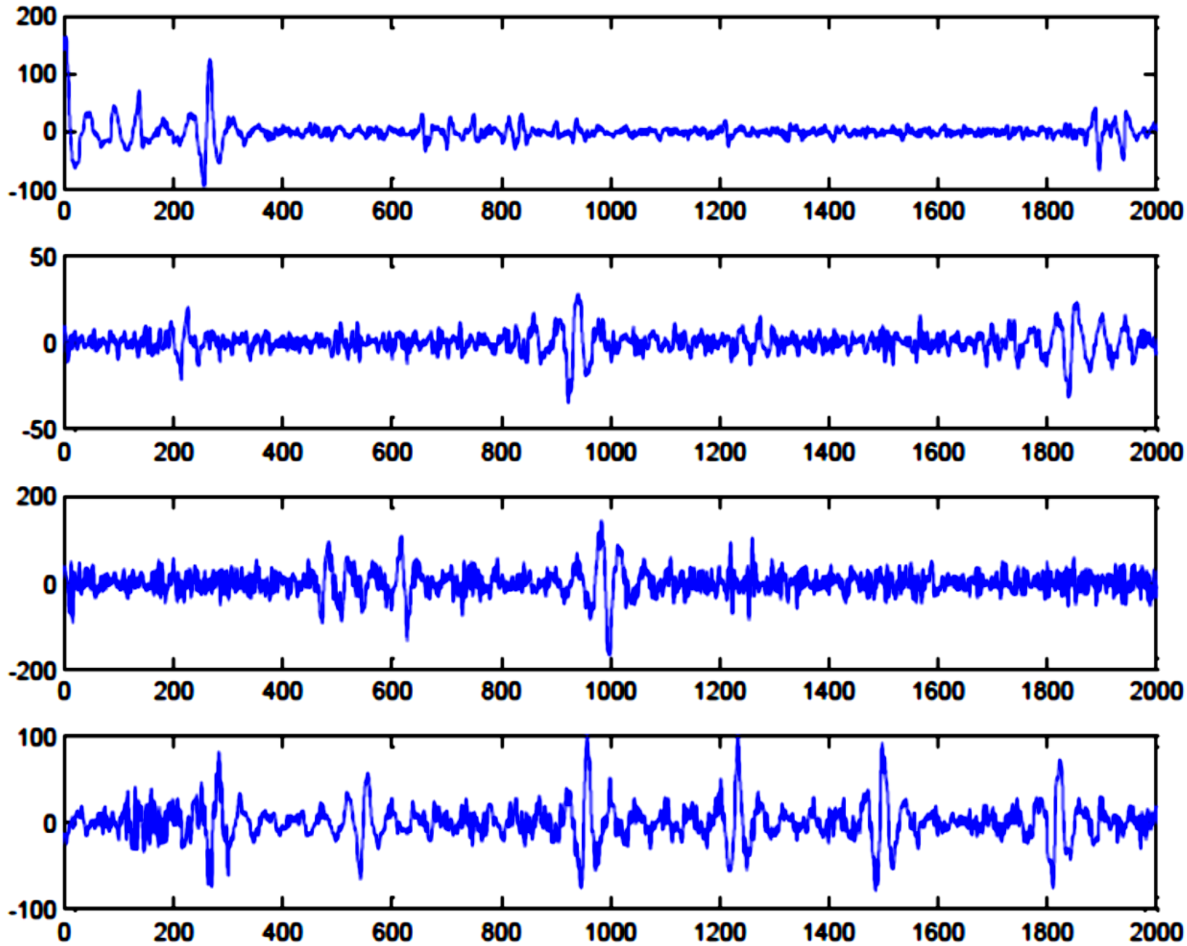
2.2. Assessment of Emotional Arousal Epochs

In this paper, we focused on EEG signals with a low range of arousal values in emotional data described above (or the subjects in the sleep). Arousal parameters were set by the ranges of 1 - 9 in emotional data corresponding to ranges of deep sleep to fully alert. We selected data with arousal values smaller than 4 in our experiments. Emotion data were surveyed to assess the abrupt shift of the EEG frequency when an emotion appeared, and the results were applied to the sleep data.

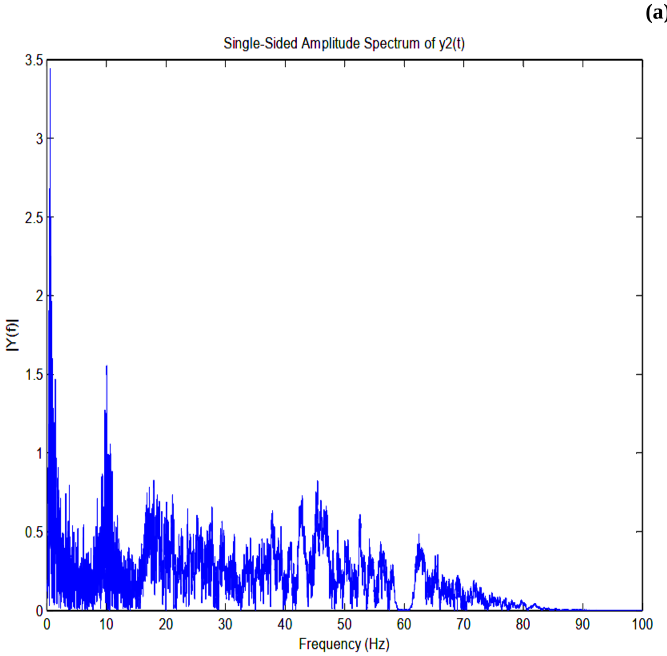
Insomnia was conceptualized as a symptom of psychopathology, as was done in ‘Sleep Medicine Reviews’, especially in relation to mood disorders. Insomnia is characterized by strong positive and negative emotions or high emotional intensity. Higher levels of emotional intensity, defined as the frequency and intensity of the expression of emotions, were linked to reduced amounts of sleep and increased nocturnal activity. Emotional intensity was also considered in our experiments based on its density and changes in shape. It was possible to observe and examine the assessments from the analysis of the EEGs.

2.2.1. Emotional EEG Segments

Based on the database of emotions, we were able to determine visually that the emergence of emotion was linked to the appearance of a pulse in wavelet types and to the values of the dominant parameter associated with the number of pulses that appeared. In some cases, it is possible to see more complex types and shapes of the signals, but the cause was the mixture of the theta, alpha, and beta waves. Each pulse appeared for a duration of 0.5 – 3 seconds, and 1-second pulses were the most common size. There were some cases in which the length of the pulse exceeded three seconds, but such pulses were formed from the combination of multiple serial pulses. The pulses can occur with high or low densities and high or medium amplitudes, and the pulse densities and amplitudes were dependent on the emotional intensity; according to the database from some researchers [13], they focused mainly on human emotions. The emotions were assessed comprehensively with 16 emotional states and many parameters with a wide range of values. Referring to those databases also gave us similar results. Thus, it was very easy to see that the emergence of emotions and their intensities were related to the EEG pulses and their densities. Figure 1.a shows four emotional segments with different dominances. However, some cases may be detected incorrectly, so a few conditions must first be met [14].



(a)



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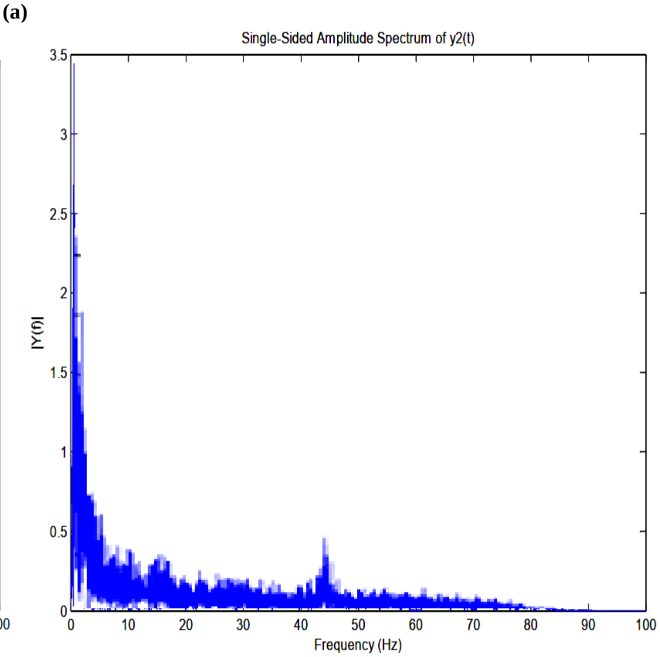


(c)

Fig. 1 Emotional arousal epochs in different intensities and densities
(a) Four emotional segments with different densities; (b) The signal spectra in case of occurrence of emotions, and (c) The signal spectrum in the absence of the occurrence of emotions.

Before an EEG arousal can be scored, subjects must be asleep, defined as > 10 continuous seconds of the indication of any stage of sleep. Arousals cannot be scored based on changes in submental (chin) EMG amplitude alone. A minimum of 10 continuous seconds of intervening sleep is necessary to score a second arousal.

A "K complex" or "spindle" (a sub-band from 12 to 14 Hz) occurring immediately before the EEG shift or following it is not included in the arousal duration. Parts of the EEG totally obscured by EMG artifact are considered as arousal if the change in the background EEG, in addition to the area obscured by EMG, is at least three seconds. The alpha activity of fewer than three seconds duration in NREM sleep at a rate greater than one burst per 10 seconds was not scored as an EEG arousal. Three seconds of alpha sleep was not scored as arousal unless a 10-second episode of alpha-free sleep precedes it.

Transitions from one stage of sleep to another are not sufficient of themselves to be scored as EEG arousals unless they meet the criteria indicated above. To assess energy distributions and the abrupt shift of EEG frequency in emotional arousal epochs, four bandpass filters were used to extract four basic EEG sub-bands, namely delta (0.5 - 4 Hz), theta (4 - 8 Hz), alpha (8 – 12 Hz) and beta (12 – 30 Hz). The power of sub-bands was checked after every segment of 200 samples.

Figure 1.b and 1.c shows an example of the signal spectra in two cases "*with and without the appearance of emotions within the one-second segments*". It can be observed that in the case where the "subject is awakening," the emergence of emotions occurs with the energy increasing suddenly at the theta or alpha bands (or both), while in the case where the "subject is sleeping," an emotion appearance was accompanied by the emergence of alpha, theta and beta waves. The frequency-amplitude spectrum of each epoch used to check the shift in EEG frequency gave us similar results.

Energy Ratio between Subbands

Following the frequency-amplitude spectrum graph, the surges of theta, alpha, and beta waves were accompanied by the reduction of the delta wave. Thus, to assess the abrupt shift in EEG frequency, we set up three parameters: R1, R2, and R3, where R1 is the ratio of the theta wave's power to the delta wave's power, R2 is the ratio of the alpha wave's power to the delta wave's power, and R3 is the ratio of the beta wave's power to the delta wave's power, i.e.,

$$R_1 = \frac{\text{power of theta wave}}{\text{power of delta wave}};$$

$$R_2 = \frac{\text{power of alpha wave}}{\text{power of delta wave}};$$

$$R_3 = \frac{\text{power of beta wave}}{\text{powerof delta wave}}$$

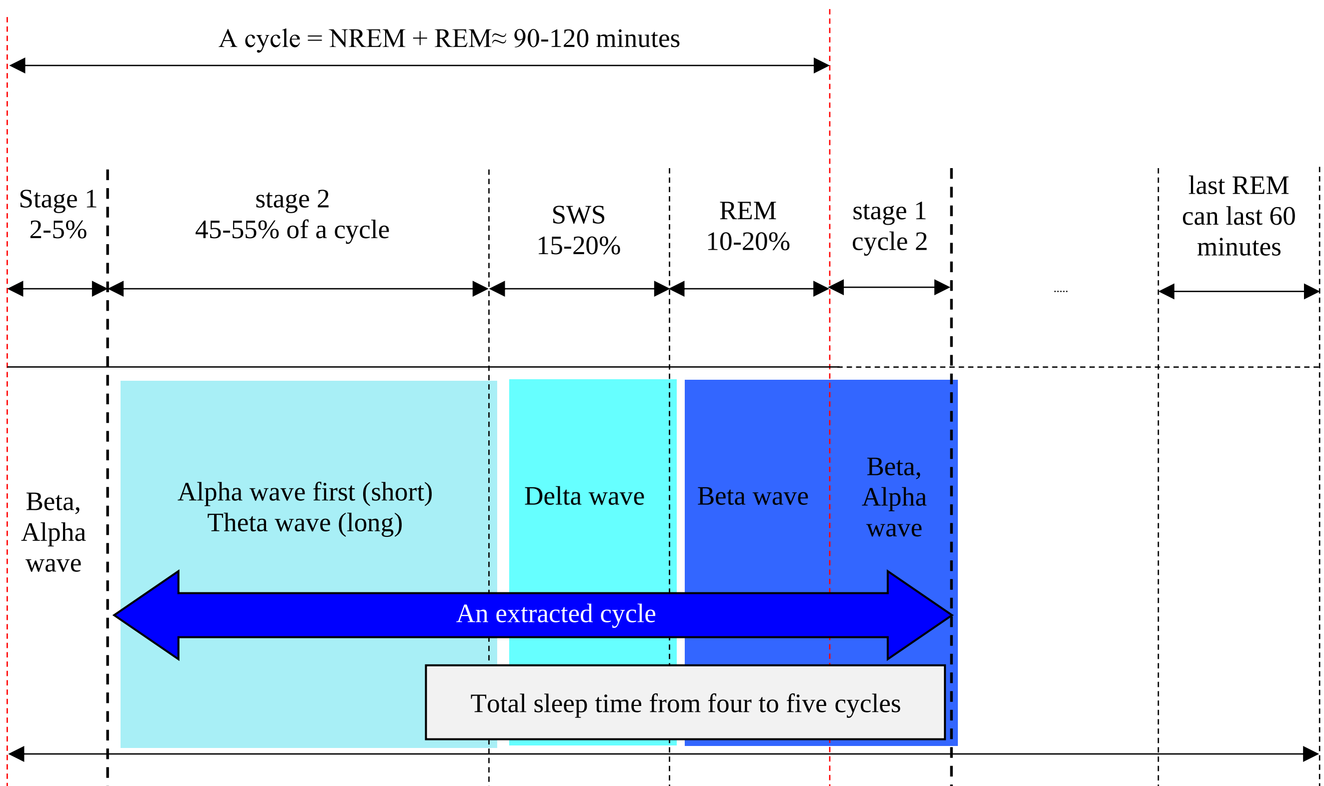


Fig. 2 Distribution of the cycles and sleep stages in nocturnal sleep

Table 2. Comparison of R_1, R_2, and R_3 values between SSEs and EAEs

		Standard Sleep Epochs (SSEs)			Emotion Arousal Epoch (EAEs)	Overlapping ranges
		stage1+REM	stage2	SWS		
R_1	range	0.067 - 0.732	0.12 - 0.47	0.042 - 0.176	0.54 - 2.27	0.54 - 0.732
	mean	0.42	0.28	0.073	1.24	
R_2	range	0.03 - 0.69	0.05 - 0.58	0.014 - 0.067	0.67 - 6.53	0.67 - 0.69
	mean	0.166	0.26	0.028	2.38	
R_3	range	0.044 - 0.623	0.02 - 0.14	0.0028 - 0.027	0.46 - 1.62	0.46 - 0.623
	mean	0.148	0.07	0.007	0.78	

We classified sleep into three stages: stage 1+REM, stage 2, and slow wave sleep based on the distribution of the stages in a sleep cycle and consecutive cycles shown in Figure 2. The EEG signal analysis was performed on each epoch, and the results were considered statistically. The range and mean values of the parameters R1, R2, and R3. Were compared between EAE and Standard Sleep Epochs (SSE).

The statistical results obtained from a total of 1200 epochs for each group of data have a $p < 0.002$. The results are shown in Table 2. By using the SSEs from a standard sleep database [13], EAEs were obtained. From Table 2, the differences among R_1, R2, and R_3 values of SSEs and EAEs are very clear, but there are overlapping ranges in the power rate values. Thus, if we apply only thresholds for R_1, R_2, and R_3 to recognize EAEs, we may have trouble with some EAEs because the R_1, R_2, and R_3 parameters are in overlapping ranges. To overcome these problems, an additional step in the checking procedure was used.

Wavelet transform: The name 'wavelet' means a small wave or a wave that does not have an infinite length (as is the case for a sinusoidal wave). As time-domain analysis of bio-signals such as EEG does not provide frequency details. EEG signals are dynamic, sometimes appearing as spikes/bursts, and they are mostly non-stationary.

Non-stationary signals are characterized by numerous transitory drift trends and abrupt changes. For practical analysis, we must know their frequency components and the time at which they occur. The wavelet transform can be viewed as transforming the signal from the time domain to the wavelet domain. This new domain contains more complicated basis functions, which are called wavelets, mother wavelets, or analyzing wavelets. If we have a signal x(t), the wavelet decomposition can be given as follows:

$$x(t) = \sum_{j=1}^{L} \sum_{k=-\infty}^{\infty} d(j,k)\psi(2^{-j}t - k) + \sum_{k=-\infty}^{\infty} a(L,K)\,\varphi(2^{-L}t - k) \quad (1)$$

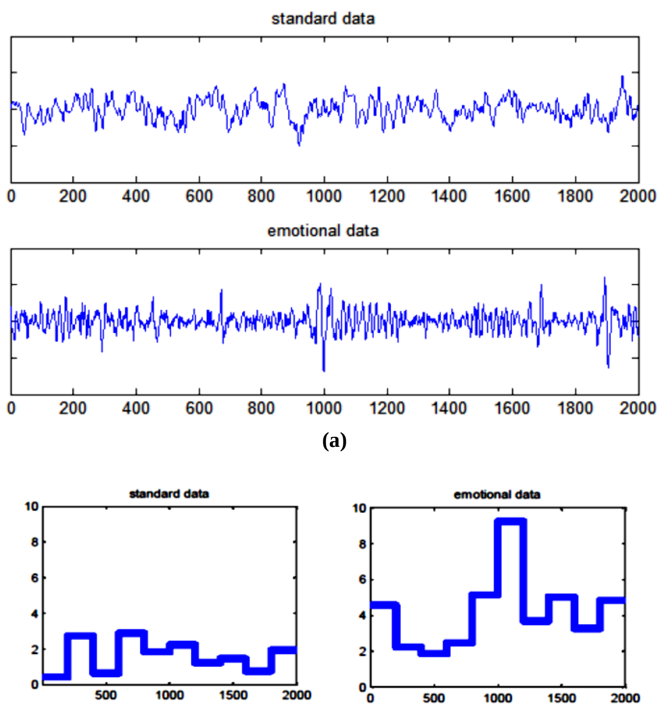
The function ψ(t) is known as the mother wavelet, while $\boldsymbol{\varphi(t)}$ is known as the scaling function. The number a(L,k) is known as the approximation coefficient at scale L, while d(j, k) is known as the detail coefficient at scale j.

Wavelet entropy: Wavelet entropy based on wavelet analysis is used to obtain the probability distribution, thereby reflecting the degree of disorder in optimal time-frequency resolution [15]. Wavelet entropy is calculated as follows:

$$\boldsymbol{E_w = -\sum_j p_j . ln(p_j)} \quad (2)$$

With P, is the probability of energy appearing at the jth wavelet coefficients, calculated by the ratio of the energy of the jth wavelet coefficient to the signal energy tone.

Calculate the wavelet entropy value for the omitted EAE when compared with the regular epochs, the results are shown in figure 3.



(b)

Fig. 3 Difference between entropy values of regular epochs and EAE
(a) Regular epochs and wavelet entropy values,
(b) EAEs and wavelet entropy values

Misrecognized epochs are mainly transient emotions of the subject. Entropy values have skyrocketed compared to epochs. Normally, EAE (Emax/Emean = 2.56 ~ 3.02; p < 0.02) compared to common epoch normal (Emax/Emean 1,532.24; p<0,02). The above statistical results have shown that wavelet entropy is a tool for detecting low-energy EAE or moments of fleeting emotions.

We can calculate the probability distribution from the wavelet decomposition equation:

$$\boldsymbol{S}(\boldsymbol{t}) = \sum_{j=-N}^{-1} \sum_{k} \boldsymbol{C}_{\boldsymbol{j}}\,(\boldsymbol{k})\boldsymbol{\psi}_{\boldsymbol{j},\boldsymbol{k}}(\boldsymbol{t}) = \sum_{j=-N}^{-1} \boldsymbol{r}_{\boldsymbol{j}}\,(\boldsymbol{t}) \quad (3)$$

The function $\boldsymbol{C_i(k)}$ is wavelet coefficients that are retained and $\boldsymbol{r_i(t)}$ is the residual signal at scale j (j, k ϵ Z). The energy at each resolution level, + j = -1, …, -N, will be the energy of the detailed signal.

$$\boldsymbol{E_j} = \|\boldsymbol{r_j}\|^2 = \sum_k |\boldsymbol{C_j(k)}|^2 \quad (4)$$

So the energy at time k will be:

$$\boldsymbol{E(k)} = \sum_{j=-N}^{-1} |\boldsymbol{C_j(k)}|^2 \quad (5)$$

The total energy can be obtained from:

$$\boldsymbol{E_{tot}} = \sum_j \boldsymbol{E_j} \quad (6)$$

From this, we can obtain the probability distribution based on relative wavelet energy:

$$\boldsymbol{p_j} = \frac{\boldsymbol{E_j}}{\boldsymbol{E_{tot}}} \quad (7)$$

From equations (1) and (6), wavelet entropy is:

$$\boldsymbol{E_w} = -\sum_j \boldsymbol{p_j} \cdot \boldsymbol{ln}(\boldsymbol{p_j}) \quad (8)$$

Relative wavelet entropy: Classical entropy-based criteria match these conditions and describe information-related properties for an accurate representation of a given signal. Many others are available and can be easily integrated. In the following expressions, s is the signal, and (si)i are the coefficients of s in an orthonormal basis. The entropy E must be an additive cost function such that E(0) = 0 and:
The “Shannon” entropy is defined as

$$\boldsymbol{E1(s)} = -\sum_i \boldsymbol{s_i^2}\,\boldsymbol{log}(\boldsymbol{s_i^2}) \quad (9)$$

The concentration in norm entropy with $\boldsymbol{1 \le p}$is defined as

$$\boldsymbol{E2(s)} = \sum_i |\boldsymbol{s_i}|^{\boldsymbol{p}} = \|\boldsymbol{s}\|_{\boldsymbol{p}}^{\boldsymbol{p}} \quad (10)$$

The "log energy" entropy is defined as

$$\boldsymbol{E3(s)} = \sum_i^{\Sigma(s_i{}^2)} \boldsymbol{log} \quad (11)$$

This study uses relative wavelet entropy and applies formula (9) to assess some EAEs that have been ignored to compare with the normal epochs of the standard data following formula (9). Each entropy value will be calculated in the duration of 200 samples. The “Shannon” entropy gives the best results in our experiments.

The entropy assessment was applied to detect EAEs when their R values were in the overlapped ranges. Those EAEs were mainly transient EAEs or other EAEs with weak intensities arousals. If the epoch were considered as EAEs, then the max entropy of the epoch (Emax) is far greater than the average entropy (Emean) (Emax/Emean ≈ 2.56 -3.02; p < 0.02) when compared with normal epochs (Emax/Emean ≈ 1.53 - 2.24; p < 0.02). With some epochs that have sleep spindles and K complex, the entropy values were considered to avoid confusion (Emax/Emean ≈ 1.84-2.24 ; p < 0.02).

The statistical results showed that the entropy assessment is a powerful tool which can detect EAEs. However, it is mainly applicable only for EAEs for which their R values were in the overlapped ranges. This method shouldn’t be applied to detect all of EAEs. Because if the R values are out of the overlapped ranges, we can determine with certainty that the epoch is an EAE or an SSE. Moreover, in the case where the intensity of emotional arousal is high enough to spread over the entire epoch, the Emax value will not be much greater than the Emean value.

2.3. Sleep Stage Recognition

A combined system of neural networks and fuzzy systems was applied to classify sleep stages [14]. For our purposes, we classified a cycle of sleep into three stages: stage 1+REM, stage 2, and slow wave sleep) based on the distribution of the cycles and sleep stages as in Figure 2. In this research, Fourier filters were used instead of wavelet transforms to decompose the inputs and extract the features. A combined system of the neural network and fuzzy systems can recognize sleep stages with high quality. However, the identification of sleep stages is done with standard epochs (sleep data without emotion). A question worth considering is, “Does this system work well in accordance with sleep data that includes sleep disturbance? The answer is that this system can work well with data of disturbance sleep or sleep data with emotion. An emergence of EAE is always accompanied by surging alpha and beta waves, so EAEs may mislead the system to incorrectly interpret sleep stages.

However, emotional arousals were focused on a few epochs, and their distributions were scattered such that they wouldn't significantly affect the recognition of sleep cycles and stages. In order to check the densities of each kind of epoch around the borders between the two stages, we assessed as closely as possible the bounds of each stage. Sleep experts performed a manual re-checking procedure to ensure that the results were correct.

Dividing total sleep into 3 stages: stage1+REM, stage2, and SWS can easily classify the sleep cycle and sleep stages with high accuracy because each stage was represented by one or two of four main waves only. Stage 1+REM are represented by Beta and Alpha waves, and stage 2 is represented mainly by Theta waves, while Delta waves represent SWS.

Table 3. Distribution of epochs in each sleep stage of the cycles

No	Stage1 and REM	Stage2	SWS	Stage1 and REM	Stage2	SWS	Stage1 and REM	Stage2	SWS	groups
cycle	1			2			3			
1	123	344	87	156	304	109	271	243	68	I
2	129	311	49	241	263	75	195	309	102	
3	101	328	92	182	286	89	152	321	73	
4	255	246	84	136	292	93	235	276	58	
mean	152	307.25	78	178.75	286.25	91.5	213.25	287.25	75.25	
5	136	302	75	135	292	128	168	284	93	II
6	89	296	82	191	305	101	225	303	109	
7	118	284	101	133	246	92	168	335	132	
8	108	340	129	121	253	84	179	281	109	
9	93	297	101	104	265	107	142	301	98	
mean	108.8	303.8	97.6	136.8	272.2	102.4	176.4	300.8	108.2	
10	85	261	114	92	268	155	118	232	104	III
11	101	236	135	85	287	109	142	288	114	
12	66	273	161	89	264	92	133	241	136	
13	83	288	140	106	301	99	85	278	173	
14	77	242	132	82	268	143	112	251	117	
mean	82.4	260	136.4	90.8	277.6	119.6	118	258	128.8	

It was easy to analyze the influence of the length of the stages on the quality of sleep. In the first cycles, stage 1 was short enough to be removed as a means of obtaining stable data. The evaluation of the number of epochs or the distribution of sleep stages in each sleep cycle was very important because the number of epochs determines the lengths of the sleep stages, and the length of the cycles or sleep stages can give us information about the quality of sleep. To find the bounds between the two stages more accurately, a manual re-checking procedure was performed by sleep experts to ensure that the results were correct. The classified results are shown in Table 3.

With more than six hours of recording data, three whole cycles were extracted that included a total of 22,071 epochs, 5,742 of which were stage 1 and REM, 11,885 of which were stage 2, and 4,444 of which were "slow-wave sleep." Stage 1 and REM are approximately 26% of the total sleep time, stage 2 is approximately 53.85%, and SWS time is approximately 20.15%.

2.4. Extraction of EAEs

This step was the most important focus of this research: the specification of the extent of the emergence of EAEs (the density of EAEs) in each sleep cycle. From the analysis mentioned above, a procedure to extract EAEs was applied. Information about the number of EAEs in each cycle was marked, and the average numbers of EAEs for every subject for each sleep cycle were summarized, listed, and classified into one of the following three groups: group 1 with the worst sleep, group 2 with normal sleep, and group 3 with good sleep. The process of extracting EAEs was conducted step by step, as described below.

Extract four sub-bands (delta, theta, alpha, and beta). Calculate the three parameters: R_1, R_2, and R_3. Compare the parameters with the thresholds in the Table 2.

- First we chose epochs that were out of the ranges of the standard epochs. Namely, the R_1 value from 0.54 to 2.27, the R_2 value from 0.67 to 6.53 and the R_3 value from 0.46 to 1.62.
- Next, we summarize the epochs where the R_1, R_2, and R_3 values are in the overlapping ranges. Namely R_1 value from 0.54 to 0.732, R_2 value from 0.67 to 0.69 and R_3 value from 0.46 to 0.623.

Apply the entropy method to detect transient EAEs. The number of EAEs for each group changed significantly, as shown in Table 4.

From Table 4, we saw that the EAEs, including normal arousal epochs and transient arousal epochs, occur mainly in stage 1, REM and stage 2. EAEs of SWS were seldom detected in our experiments. In some cases, it appeared that the EAEs of SWS were mostly due to transient arousal, and they caused the phenomenon of a confused state. These results were in agreement with the results of other research that investigated emotional arousal in slow-wave sleep [16]. They are often sudden arousals with a piercing scream or cry, such as the phenomenon of sleep terror, and such arousals are usually accompanied by autonomic and behavioral manifestations of intense fear, and they are rarely forgotten by anyone who witnesses such an event. The onset of these events is abrupt, and subjects would have tachycardia, tachypnea, flushing, diaphoresis, and mydriasis. The subjects often wind up confused and disoriented, and any attempts to intercede may result in harm to the person who is trying to wake the patient. Patients can become violent, resulting in injury to themselves and their bed partners. Our method was implemented as follows: The first step, After receiving EEG data from the subjects, EAEs were detected, marked their position then removed out of the input data to gain clean data for the procedure of sleep stage recognition. The checking to detect EAEs is based on three parameters, R1, R2, and R3, combined with entropy value assessment. After identifying EAEs in the input data, the next procedure that needs to be done is marking the positions of the EAEs in the surveyed data segment and then removing all of the EAEs to gain clean data for the process of stage sleep stages recognition. The next step is that we must total the number of EAEs in each stage. After the classification of sleep stages and defining boundaries between stages, EAEs positions that were previously marked can tell us about the EAEs corresponding to each sleep stage. By the way, every sleep cycle is also classified, and information about the number of EAEs in each cycle can also be defined. With the process of recognizing EAEs in each sleep stage, Our classifier achieved an average accuracy of 87.5%.

3. Method Results and Discussion

3.1. Results

14 subjects, including six males and eight females, participated in these experiments. Sleep cycles and sleep stages were classified by a combination system of the neural network and fuzzy systems using only one EEG channel (C3-A1). Three sleep cycles for each subject and three stages for each cycle provided a total of 22,071 sleep epochs (SEs). A total of 1,052 EAEs were obtained, with 537 EAEs in four subjects of group 1, 365 EAEs in the five subjects of group 2 and 150 EAEs in the five subjects of group 3. The average number of sleep epochs and emotional arousal epochs that were calculated in every cycle for each subject are summarized in Table 5. The comparison table helped us determine the lengths of the cycles and the distribution of the sleep stages by determining the densities of the EAEs. The number of EAEs in each cycle clearly changes following the three levels of sleep quality, accompanied by the varying sleep-stage durations. The highest densities of EAEs were those related to disrupted sleep continuity, including a prolonged latency to REM and stage 2 sleep, an increase in nocturnal awakenings, and a decrease in the amount of total sleep toward the end of the night when sleep pressure has largely abated. Much attention has been focused on changes in REM sleep, particularly the reduced latency of the onset of REM sleep. It has long been thought to represent a marker for patients' moods and their complaints about insomnia and/or decreased need for sleep. It was found that the total number of slow waves was only slightly lower during late sleep than during early sleep. When EAE density is high (which may be related to a bad of insomnia), stage1 and REM may be longer, along with prolonged latency to stage1, and REM sleep might be the shortening SWS and vice versa. Hence, the reduced time of SWS resulted in serious mood symptoms for patients. During episodes of depression, patients usually report insomnia, including early morning awakenings. However, patients with typical depression may complain of excessive sleepiness.

However, decrements in SWS have been consistently demonstrated in mood and other psychiatric disorders as well. Loss of SWS is often seen in primary insomnia [16], and thus, it is not surprising that it might also be present in other disorders for which insomnia is a major symptom. Moreover, from the redistribution of the length of the sleep stage, it seems that the lengths of the sleep cycles are changed during high densities of EAEs. These remarks are intended only as preliminary observations, and we plan to explore this subject in more detail in future research.

3.2. Discussion

The sleep quality was classified into three groups, i.e., worst sleep, normal sleep, and good sleep. The densities of EAEs were assessed and summarized for each case. In our research, two parameters were considered (the number of EAEs focusing on each sleep cycle and the duration of slow-wave sleep), and their relationship was used to rate sleep quality. Our results were in good agreement with the findings in previous research [17,18], and they indicated that the interaction between sleep and its effect on regulatory systems is modulated and integrated in regions of the prefrontal cortex. Sleep loss induces alterations in goal-directed behaviors by weakening the influence of the prefrontal cortex over other regions of the brain. This results in the reduced modulation of emotions, drives, and impulses.

Table 4. Distribution of EAEs in each sleep stage of the cycles

Cycles	1	2	3	groups
1	51	42	46	I
2	39	43	37	
3	53	45	38	
4	43	48	52	
total	186	178	173	537
mean	46.5	44.5	43.25	
5	31	22	30	II
6	18	21	28	
7	21	17	21	
8	25	19	26	
9	28	23	35	

total	123	102	140	365
mean	24.6	20.4	28	
10	9	9	17	III
11	11	13	18	
12	8	12	11	

13	10	4	7	
14	4	7	10	
total	42	45	63	150
mean	8.4	9	12.6	

Table 5. Average number of EAEs and SEs following sleep quality levels

No	**Stage 1 and REM**	**Stage2**	**SWS**	**Stage 1 and REM**	**Stage2**	**SWS**	**Stage 1 and REM**	**Stage2**	**SWS**	**Groups and a total of EAEs**
	1			2			3			
ANSEs	152	307.25	78	178.75	286.25	91.5	213.25	287.25	75.25	I
ANEAEs	46.5			44.5			43.25			537
ANSEs	108.8	303.8	97.6	136.8	272.2	102.4	176.4	300.8	108.2	II
ANEAEs	24.6			20.4			28			365
ANSEs	82.4	260	136.4	90.8	277.6	119.6	118	258	128.8	III
ANEAEs	8.4			9			12.6			150
	for ANSEs: average number of SEs and ANEAEs: average number of EAEs									

During the emergence of EAEs, there were increases in alpha and beta waves, and this made the subjects drift into SWS in some cases. Suppose beta waves are focused with high densities in SWS. In that case, subjects will experience sudden arousal from SWS, and that will be accompanied by autonomic and behavioral manifestations of intense fear, which are rarely forgotten by anyone who has experienced the event. The onset of the event is abrupt, and patients may have tachycardia, tachypnea, flushing, diaphoresis, and mydriasis, and the subjects typically will feel groggier.

The patients are confused and disoriented, and any attempts to intercede may result in harm to the person trying to wake the patient. Much sleep transfers from SWS to REM, which causes the prolonged latency of REM and the shortening of SWS, so the sleep cycle may be reduced. If EAEs focused on stage1 and REM or stage 2 when subjects were in dissociated sleep states, the arousal factors would be in the transition from this stage to other stages of NREM, between wakefulness and NREM sleep or wakefulness and REM sleep. The bad mood during sleep causes sleepers difficulty in drifting into SWS. In this case, stage1 REM or stage 2 may be prolonged, which leads to the reduction of SWS time, which decreases the quality of sleep.

As we know, REM sleep is the stage with a surge of beta waves, and when subjects leave NREM sleep, dreams may begin to occur. During this time, the patient's mood is active and some EAEs will occur. However, a high density of EAEs is related to abnormalities in REM sleep. Abnormalities in the parameters of REM sleep are also significantly associated with mood disorders. A few examples are: short REM latency has been associated with increased risk for relapse, and increased REM sleep has been related to increases in cholinergic activity, which also indirectly causes the decrease of SWS time due to the increased activation of the thalamus and cortex during sleep [19]. The quality of sleep is actually related to many factors, including heart rate, respiratory rate [20, 21], and a combination of several other psychophysiological signals.

According to McCrae et al. (2008) [11] and Norlander et al. (2005) [12], sleep quality is related to both poles of emotion, Negative Emotion (NE) and Positive Emotion (PE), with a higher PE correlating to a higher self-reported sleep quality and less wake time, and a higher NE with a lower PE correlating with a lower self-reported sleep quality and greater wake time. However, based on our research, high PE and NE are actually associated with high densities of EAE and low PE and NE are associated with low densities of EAE. So, a proper method could be to focus on emotional arousal densities. Based on the discussion above, we can conclude that the number of emotional arousal epochs or EAEs' densities actually influence the distribution of the durations of the sleep stages and sleep quality.

4. Conclusion

This study proposed a method to evaluate sleep quality based on EEG signals, and the preliminary results were satisfactory for our purposes. In this research, we focused on a single parameter, which is emotional arousal. Sleep quality was assessed based on emotional arousal densities, or the number of EAEs converged on each sleep cycle. Also, only one emotion parameter (emotional arousal) was mentioned.

However, the valence values of emotion (from unhappy to happy) or negative emotion and positive emotion also closely relate to the quality of sleep. Furthermore sleep quality was evaluated based on each sleep cycle. For this reason, in order to improve the assessment of sleep quality, a full assessment will be included in our future studies with the consideration of many related psychophysiological parameters. The data samples, subjects and the length of sleep intervals will be increased in our future experiments to improve the assessment quality.

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References

[1] Charles Adedayo Ogunbode et al., "Negative Emotions about Climate Change are Related to Insomnia Symptoms and Mental Health: Cross-Sectional Evidence from 25 Countries," *Current Psychology*, vol. 42, pp. 845-854, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[2] M. Camaioni et al., "EEG Patterns Prior to Motor Activations of Parasomnias: A Systematic," *Nature and Science of Sleep*, vol. 13, pp. 713-728, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[3] Anthony Kales, and Allan Rechtschaffen, *A Manual of Standardized Terminology, Techniques and Scoring System for Sleep Stages of Human Subjects*, United States Government Printing Office, Washington, 1968. [Google Scholar] [Publisher Link]

[4] Yuta Senzai, and Massimo Scanziani, "A Cognitive Process Occurring during Sleep is Revealed by Rapid Eye Movements**,"** *Science*, vol. 377, no. 6609, pp. 999-1004, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[5] Aakash K. Patel et al., *Physiology, Sleep Stages*, StatPearls Publishing, 2022. [Google Scholar] [Publisher Link]

[6] Mustafa H. Gandhi, and Prabhu D. Emmady, *Physiology, K Complex*, StatPearls Publishing, 2023. [Google Scholar] [Publisher Link]

[7] Chris Drew, "Schachter-Singer Theory – Examples and Definition," *Helpful Professor*, 2023. [Google Scholar] [Publisher Link]

[8] Bibek Karna, Abdulghani Sankari, and Geethika Tatikonda, *Sleep Disorder*, StatPearls Publishing, 2023. [Google Scholar] [Publisher Link]

[9] Divya Garg, and Gyanendra K. Verma, "Emotion Recognition in Valence-Arousal Space from Multi-Channel EEG Data and Wavelet Based Deep Learning Framework," *Procedia Computer Science*, vol. 171, pp. 857-867, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[10] Jiaojiao Lu, Yan An, and Jun Qiu, "Relationship between Sleep Quality, Mood State, and Performance of Elite Air-Rifle Shooters," *BMC Sports Science, Medicine and Rehabilitation*, vol. 14, pp. 1-8, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[11] Radu Lefter et al., "Interactions between Sleep and Emotions in Humans and Animal Models," *Medicina*, vol. 58, no. 2, pp. 1-17, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[12] Victor Menezes Silva, Joedyson Emmanuel de Macedo Magalhaes, and Leandro Lourenção Duarte, "Quality of Sleep and Anxiety are Related to Circadian Preference in University Students," *PLoS One*, vol. 15, no. 9, pp. 1-11, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[13] Can Deng et al., "Emotion Recognition Positively Correlates with Steady-State Visual Evoked Potential Amplitude and Alpha Entrainment," *Neuroscience*, vol. 434, pp. 191-199, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[14] Giuseppe Loddo et al., "Disorders of Arousal in Adults: New Diagnostic Tools for Clinical Practice," *Sleep Science Practice*, vol. 3, pp. 1-13, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[15] Divyanshu Dwivedi, Ashutosh Chamoli, and Sandip Kumar Rana, "Wavelet Entropy: A New Tool for Edge Detection of Potential Field Data," *Entropy*, vol. 25, no. 2, pp. 1-18, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[16] Maëva Moyne et al., "Brain Reactivity to Emotion Persists in NREM Sleep and is Associated with Individual Dream Recall," *Cerebral Cortex Communications*, vol. 3, no. 1, pp. 1-20, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[17] Marie Vandekerckhove, and Yu-lin Wang, "Emotion, Emotion Regulation and Sleep: An Intimate Relationship," *AIMS Neuroscience*, vol. 5, no. 1, pp. 1-17, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[18] Yanjing Wang et al., "Changes in Ventromedial Prefrontal Cortex Functional Connectivity are Correlated with Increased Risk-Taking after Total Sleep Deprivation," *Behavioural Brain Research*, vol. 418, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[19] Y. Audrey Hay et al., "Thalamus Mediates Neocortical Down State Transition via GABAB-Receptor-Targeting Interneurons," *Neuron*, vol. 109, no. 17, pp. 2682-2690, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[20] Sirinthip Roomkham et al., *Technologies for Quantifying Sleep: Improved Quality of Life or Overwhelming Gadgets*?, Quantifying Quality of Life, pp. 151-164, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[21] Dan Guo et al., "ECG-Derived Cardiopulmonary Analysis of Pediatric Sleep-Disordered Breathing," *Sleep Medicine*, vol. 12, no. 4, pp. 384-389, 2011. [CrossRef] [Google Scholar] [Publisher Link]