International Journal for Multidisciplinary Research (IJFMR)

E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

Sleep Spindles Using Electroencephalography Signals

Anchal Agrawal[1], Dr. Raghavendra Prasad[2]

[1,2]Amity University Chhattisgarh

Abstract:

EEG stands for electroencephalography. It is a non-invasive neurophysiological technique that and amplify the tiny electrical signals produced by neurons. A medical imaging method called electroencephalography measures the electrical activity in the scalp that is produced by brain regions (Teplan, 2002). Short oscillations known as sleep spindles can be seen in the human electroencephalogram (EEG) when a person is sleepy or drowsy (Lüthi, 2014). Neither the topography nor the morphology of sleep spindles remains constant throughout the lifespan (Clawson et al., 2016). Sleep spindles frequency range is between 12 Hz and 14 Hz. This frequency was extended to 11 Hz to 16 Hz after the American Academy of Sleep Medicine (AASM) published a new version of their sleep scoring guidelines in 2002 [37,16,15,43,23] One of the two primary sleep cycles that comprise a full sleep cycle is called NREM (Non-Rapid Eye Movement), the other being REM (Rapid Eye Movement) sleep. There are three stages of NREM sleep: N1, N2, and N3 (Al-Salman et al., 2019). With a sensitivity ranging from 89.1% to 100%, deep learning techniques have been developed to detect sleep spindles using 11 to 30 adult sleep EEGs [21, 23]. However, current sleep spindle detection methods based on deep learning Techniques do not quantify both the quantity and length of sleep spindle events. The disconnection between the classifier's output and signal features, which can be directly linked to the underlying physiological and physical processes, is another acknowledged limitation of deep learning techniques [24, 25]. This makes it challenging to interpret deep learning-based sleep spindles detection methods and may have a detrimental effect on users' trust (Wei et al., 2022).

Keywords: Sleep Spindles, electroencephalography (EEG), Non Rapid Eye Movement(NREM)

Introduction:

In order to help doctors and researchers analyze baby sleep spindles, the Deep-spindle system displays the start and end times of sleep spindles in lengthy EEG recordings. It also provides information on the amplitude, PSD, and spectrogram of any detected sleep spindle. It is anticipated that Deep-spindle would find widespread use in many therapeutic settings, therefore reducing time and labor-intensive manual annotation (Jaramillo et al., 2023). Because variations in spindle characteristics (such as density, frequency, shape, and spatial distribution) help identify a number of sleep disorders, including sleep apnea, insomnia, narcolepsy, restless leg syndrome, and parasomnias, sleep spindles are significant from a clinical standpoint. Children with sleep disordered breathing , adults with idiopathic narcolepsy, hypersomnia , and restless leg syndrome (RLS) all had their EEG signals investigated for sleep spindle feature (Eltrass & Ghanem, 2023). Most, if not all, animals go through periodic sleep, which is a behavioral state. From an evolutionary point of view, it's dangerous to sleep. Our vulnerability to predators increases as our minds grow disconnected from the outside world. So why do people, for example, sleep for around one-third of their lives? (Bandarabadi et al., 2020)Everyone agrees that sleep is essential for sustaining our mental faculties in addition to being pleasurable for our body. Our brain's many networks interact in radically different ways when we go from awake to sleep. Significantly, in the waking state, the thalamus, a subcortical area, transmits sensory data to the cerebral cortex Uma and associates (Ujma et al., 2015), alters its activity when we sleep, causing us to become unconscious. We may also see sleep-specific patterns in electrical brain activity recordings, which are a manifestation of this changed network state. The brain produces slow, high-amplitude waves as we sleep, along with sporadic bursts of higher frequency activity known as sleep spindles, in contrast to the rapid mixed-frequency activity that characterizes waking. It's interesting that sleep's significant impact on cognitive performance has been connected to these oscillations(Clawson et al., 2016).What are sleep spindles? During non-rapid eye movement sleep, discrete bursts of rhythmic brain activity in the frequency range of 11 to 16 Hz are known as sleep spindles(Al-Salman et al., 2019)When do spindles in sleep happen? A crucial factor in establishing the commencement of NREM sleep is the presence of sleep spindles. As soon as we shift from the transitional stage of sleep onset into the light phases of non-REM sleep, they become apparent. They are then produced on a regular basis, roughly every three to six seconds. Spindles don't happen during REM sleep, although they do happen during deep slow wave and mild NREM sleep. Sleep spindles can be seen on their own, as they frequently are during light sleep, but they also preferentially coincide with the up-states of high-amplitude slow waves (Lüthi, 2014).

Brain signal-grounded emotion discovery holds significant pledge in revolutionizing the opinion and operation of colorful medical conditions. Traditional styles of emotion identification, similar as facial expressions, may encounter challenges with limited triggers, emotional disguises, or conditions like alexithymia.(Chambayil et al., 2010) This study explores the eventuality of exercising electroencephalogram(EEG) data to crack emotional countries by assaying constant brainwaves, furnishing perceptivity into feelings that individualities might struggle to articulate verbally.(Tyagi, 2012) The exploration focuses on assaying time data from EEG detector channels and conducting relative assessments of colorful machine literacy ways. The study evaluates machine literacy algorithms, including Support Vector Machine(SVM), K- nearest Neighbor, Linear Discriminant Analysis, Logistic Regression, and Decision Trees.(Abo-Zahhad et al., 2015b) Both with and without top element analysis(PCA) for dimensionality reduction, these ways are tested. To optimize the models, grid hunt and hyperactive-parameter tuning are enforced, using a Spark cluster to reduce prosecution time. The DEAP Dataset, a multimodal dataset designed for probing mortal affective countries, is employed for this disquisition.(Tyagi, 2012)

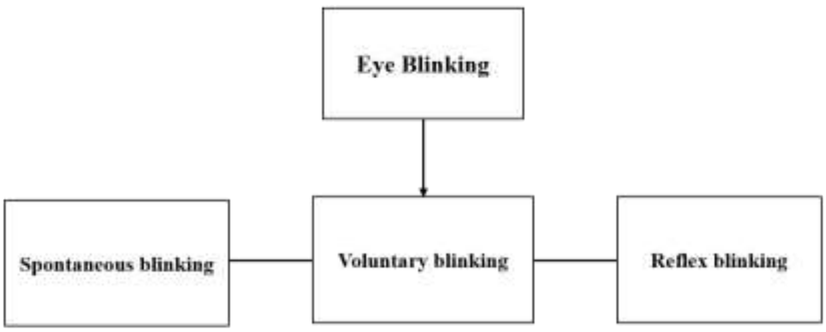

Fig1 : Types of EYE Blinking

Literature Review:

Brodmann Area:

Through using Brodmann's areas, the cortex of the brain can be divided into 52 areas which are numbered sequentially. These areas are distinguished by microscopic anatomy through the shapes and types of cells and their connections.

Broadmann Area	Cortex	Work
1,2,3	Primary somatosensory	responsible for processing somatic sensations(Wu et al., 2023).
4	Primary Motor	involved in the execution of movement (Guttmann-Flury et al., 2023).
5	Somatosensory Association	an area for sensory input (Pazhoohi et al., 2023)
6	Premotor and Supplementary Motor	helps to control and plan movements
7	Somatosensory Association	an area for sensory input
8	Frontal eye fields	role in the control of visual attention and eye movements.
9	Dorsolateral prefrontal	involved in cognitive functions such as working memory, attention, and executive function.
10	Anterior prefrontal	higher cognitive functions such as task management and planning.
11,12	Orbitofrontal Area (orbital gyri, gyrus rectus, rostral gyrus and part of superior frontal gyrus)	receives information about the sight of objects as well as the reward value of taste.
13,16	Insular Cortex	sensory processing, decision-making, and motor control.
17	Primary Visual Cortex (V1)	interpreting and processing visual information received from the eyes
18	Secondary Visual Cortex (V2)	receives visual information for further analysis
19	Associative Visual Cortex (V3, V4 & V5)	complex processing of visual information.
20	Inferior Temporal Gyrus	processes visual information in the field of vision and is involved with memory.
21	Middle Temporal Gyrus	semantic memory processing, visual perception, and language processing.
22	Superior Temporal Gyrus (including Wernicke's Area)	important for processing sounds and comprehension of speech.

23,24,28,33	Cingulate Gyrus	a part of the limbic system which is involved in processing emotions and behavior regulation.
25	Subgenual Area	a limbic area rich in serotonin transporters which works with the other areas of the limbic system
26	Ectosplenial portion of the retrosplenial region of the cerebral	related to motor learning
27	Piriform cortex	related to the sense of smell
29	Retrosplenial cingulate	related to episodic memory and navigation.
30	Part of the cingulate cortex	an interface between emotional regulation, sensing and action.
31	Dorsal posterior cingulate	– a central node of the default mode network (DMN), a set of brain structures with strong associations for activity during many cognitive tasks.
32	Dorsal anterior cingulate	processing the detection and appraisal of social processes.
34	Dorsal Entorhinal	involved in working memory.
35,36	Dorsal entorhinal	involved in working memory. Area 35 & 36 – Perirhinal cortex and ectorhinal area – involved in working memory
37	Fusiform gyrus	involved in higher-level visual processing.
38	Temporal pole	high-level visual area involved in visual cognition, face recognition, and visual memory.
39	Angular gyrus	a role in phonological processing and emotional responses.
40	Supramarginal gyrus	a role in phonological processing and emotional responses.
41,42	Primary auditory cortex	first relay station of auditory information in the cortex.
43	Primary gustatory cortex	responsible for the perception of taste.
44	Part of Broca area (pars opercularis, part of the inferior frontal gyrus)	associated with speech production and articulation.
45	Part of Broca area (pars triangularis, part of the inferior frontal gyrus)	associated with speech production and articulation.

46	Dorsolateral Prefrontal Cortex	involved in cognitive functions such as working memory, attention, and executive function.
47	Pars orbitalis, part of the inferior frontal gyrus	role in the processing of language.
48	Retrosubicular area	processing of emotions, encoding, and navigation.
52	Parainsular area	related to attention and salience processing.

Table 1: 52 Brodmann's Area Cortex and Work

EEG Signals:

The brain's electrical activity is recorded from the scalp using an electroencephalogram, or EEG. The waveforms that were captured show the electrical activity in the cortex. Signal intensity: The microvolt (mV) measurement of EEG activity is relatively low. Signal frequency: The human EEG wave's primary frequencies are: (Kamble & Sengupta, 2023)

Delta: has a frequency of no more than 3 Hz. It usually has the slowest waves and the largest amplitude. In newborns up to a year old and during sleep stages 3 and 4, it is typical for this to be the prevailing rhythm. It might manifest as widespread lesions, metabolic encephalopathy, hydrocephalus, or deep midline lesions, or it can manifest focally as subcortical lesions. In adults, it is often more noticeable frontally (FIRDA, or frontal intermittent rhythmic delta), whereas in children, it is typically more noticeable posteriorly (ORIRDA, or occcipital intermittent rhythmic delta).(Lin & Lin, 2023)

Theta: has a frequency of 3.5 to 7.5 Hz and is classified as "slow" activity. It is perfectly normal in children up to 13 years and in sleep but abnormal in awake adults. It can be seen as a manifestation of focal subcortical lesions; it can also be seen in generalized distribution in diffuse disorders such as metabolic encephalopathy or some instances of hydrocephalus.(Citation Venkata Phanikrishna et al., 2021)

Alpha: The frequency range of alpha is 7.5–13 Hz. is often most prominent at the back areas of the head on both sides, with the dominant side having a larger amplitude. It manifests when you close your eyes and unwind, and it vanishes when you open them or become awake by any method (such reasoning or math). It is the primary rhythm observed in typically laid-back folks. It is there throughout the most of life, but becomes more pronounced after the age of thirteen (Mizokuchi et al., 2023)

Beta: "Fast" activity is referred to as beta activity. It operates at a frequency of 14 Hz or higher. It is often distributed symmetrically on both sides, with the front being the most noticeable. Sedative-hypnotic medications, particularly benzodiazepines and barbiturates, aggravate it. Areas with cortical injury may have less of it or none at all. Most people consider it to be a typical beat. In patients who are awake, nervous, or who have their eyes open, this is the predominant rhythm (Olmez et al., 2023)

Eye Movement

Because it causes alterations in electrical conductivity and related muscular abnormalities, eye blinking presents difficulties for EEG recordings.(Abo-Zahhad et al., 2015b) Facial muscle contractions during blinking can introduce electromyographic aberrations that may cause EEG readings to become distorted.(Tyagi, 2012) These noise sources can appear as low-frequency elements, especially in the delta and theta bands, where they may obscure real brain activity. When an eye blinks, adjacent electrodes may be impacted, resulting in both vertical and horizontal distortions. Researchers use a variety of preprocessing methods to solve these issues. (R. N. Roy et al., 2014) Low-frequency components are eliminated via high-pass filtering, and blink-related aberrations can be effectively separated from EEG signals using Independent Component Analysis (ICA). While electrode selection, reference techniques, and sophisticated interpolation methods help to minimize the influence of eye blink artifacts, epoch and thresholding procedures help to identify and reject contaminated segments.(Chambayil et al., 2010)

Accurate EEG analysis requires an understanding of and mitigation of these aberrations, especially in applications such as Brain-Computer Interfaces (BCIs) where accurate brain signal interpretation is critical.(A. Roy et al., 2014) Comparison of Traditional Machine Learning styles The exploration ideal extends to the comparison of traditional machine literacy styles, assessing their performance grounded on p- value, minimal error, delicacy, perfection, and f- score. This relative analysis aims to identify the most effective approach for emotion discovery, considering the unique challenges posed by EEG signals. Traditional machine literacy styles were named for their established performance criteria and interpretability. (Jebelli et al., 2018)

Dimensionality Reduction and Information Discovery To enhance performance and discover retired information, the exploration explores the use of dimensionality reduction ways. The analysis includes a comparison of artificial neural networks(ANN) and deep neural networks(DNN) against traditional machine literacy styles. In certain scripts, ANNs and DNNs have demonstrated superior performance, attributed to their capability to capture intricate patterns within high- dimensional datasets.(Schalk et al., 2010)

Experimental Design and Data Preprocessing The degree of each sample was reduced by grading feelings into three distinct groups positive, neutral, and negative. This categorization eased a more focused analysis, allowing experimenters to claw into the specific nuances associated with each emotional state. Data preprocessing played a pivotal part in preparing the EEG signals for analysis, icing the junking of noise and vestiges that could intrude with accurate emotion discovery.(Khosla et al., 2020)

Frequency:

Repetitive action with a rhythm is referred to as frequency (in Hz). Several characteristics can be associated with the frequency of EEG activity, such as:

- Synchronous. EEG activity that is composed of roughly periodic waves.
- Rhythmic. EEG activity lacking any consistent rhythms.
- Discordant. rhythms and/or patterns of EEG activity that are either infrequently observed in healthy persons or that are typical in sick groups (Nottage et al., 2023)

Voltage:

The average or peak voltage of EEG activity is referred to as voltage. Values vary depending on how they are recorded. The following descriptive words relate to EEG voltage:

Attenuation (sometimes known as depression or suppression). EEG activity amplitude reduction brought on by a drop in voltage. Activity is considered to have "blocked" or to exhibit "blocking" when stimulus causes it to diminish. (Ahammed & Ahmed, 2020)

2. Incongruity. seen as an alpha, beta, or theta range rise in voltage and regularity of rhythmic activity. The phrase suggests that there are more brain components influencing the rhythm. (Note: word is used to describe change in the EEG, but it is also used interpretatively) (Yuan et al., 2023)

Features of spindles during sleep:

Frequency: The normal frequency range for sleep spindles is 11–16 hertz (Hz). This indicates that 11–16 cycles per second is the oscillation rate of brain waves during a spindle phase. Sleep spindles often last a few seconds, making them comparatively brief occurrences. Although the length might vary, they are usually thought to be short in comparison to other sleep patterns. (Wang et al., 2021)

Amplitude: Sleep spindles show a distinctive rise in amplitude or height on the EEG in addition to their greater frequency. This sets them apart from the ambient brain activity. (Chambayil et al., 2010)

Location: Sleep spindles are commonly seen in the central cortex, or the brain's center regions, on electroencephalograms. (Chambayil et al., 2010)

Function in Sleep: It is thought that sleep spindles contribute to information processing and memory consolidation. They have to do with the movement of data from short-term to long-term memory. (Chambayil et al., 2010)

Age-Related Changes: As people age, their sleep spindle properties might also alter. As a person ages, they often tend to become more frequent and less amplitude. .(Mannan et al., 2016)

A suggested method for keeping an eye on sleep spindles

Advanced EEG monitoring technologies and algorithms may be used in a system for tracking and evaluating sleep spindles. These instruments would be made to automatically identify, measure, and examine sleep spindles. (Hagemann & Naumann, 2001)

Real-time monitoring features might be included in the suggested system, enabling researchers or physicians to continually measure sleep spindle activity while a patient is asleep. (Haak et al., 2009)

To improve sleep spindle recognition and analysis accuracy, the system might use machine learning algorithms and advanced signal processing techniques. (Singla et al., 2011)

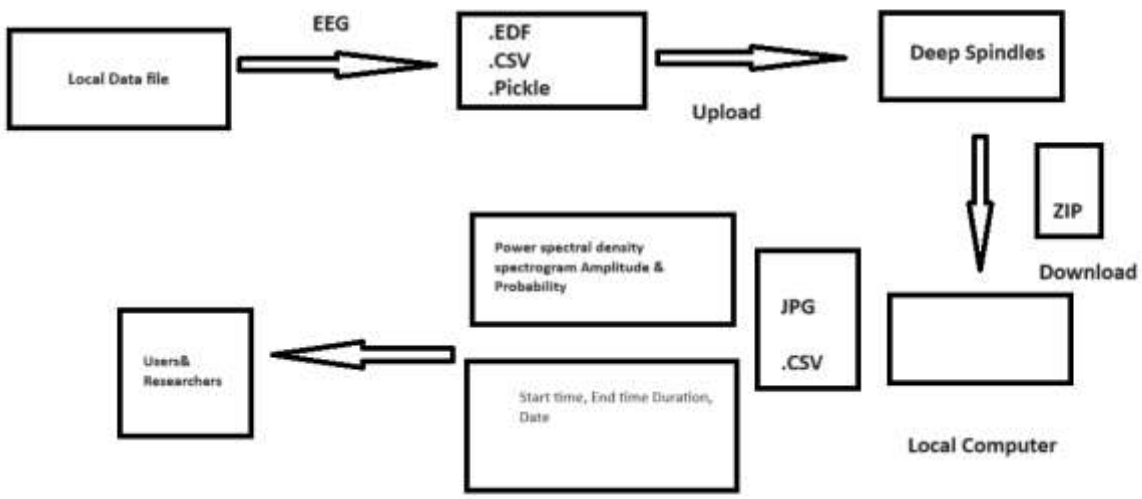

Fig2: Deep Spindles flowchart

The aim of the sleep spindle study is:

Understanding the neurophysiological mechanisms underlying sleep, especially memory consolidation and information processing, is the main goal of research on sleep spindles.

Researchers may utilize the sleep spindle data to comprehend the potential consequences of alterations in these rhythms. (Hagemann & Naumann, 2001)

EEG Channels

CHANNEL LABLE	BRAIN REGION
Fp1	Frontopolar
Fp2	Frontopolar
F3	Frontal
F4	Frontal
C3	Central
C4	Central
P3	Parietal
P4	Parietal
O1	Occipital
O2	Occipital
F7	Frontotemporal
F8	Frontotemporal
T3	Temporal
T4	Temporal
T5	Parietotemporal
T6	Parietotemporal
Fz	Frontocentral
Cz	Central
Pz	Parietal
Oz	Occipital

Table 2: EEG Channels

Future Scope

The field of EEG-based stress detection has enormous promise for revolutionary developments in both theory and real-world applications. We believe that as technology develops further, more complex algorithms that are able to identify individualised and nuanced patterns in EEG data will be refined and developed, improving the precision and dependability of stress identification. Connectivity with wearable technology and smartphone apps may open the door to real-time tracking and prompt feedback, enabling people to take charge of their stress management. Furthermore, there are a lot of intriguing opportunities for immersive and customised stress intervention techniques at the nexus of EEG and other cutting-edge technologies like virtual reality and artificial intelligence. Beyond stress detection, EEG's future applications could include neuro feedback and insights into a range of cognitive and emotional states including brain-computer connections and training. The combination of neuroscience, engineering, and data science is set to spark revolutionary breakthroughs and usher in a new era of comprehending and improving human cognition and well-being as multidisciplinary collaboration blossoms.

Computation

When processing and analyzing the electrical activity of the brain that has been recorded, an electroencephalogram (EEG) calculation usually consists of multiple phases.

Machine Learning:

In order to convert raw EEG signals into features appropriate for training and assessing machine learning models, a sequence of procedures must be followed during the computation of EEG in machine learning.(Peng et al., 2013) The first preprocessing processes are normalization for uniform scaling, filtering to identify particular frequency bands, and eliminating artifacts like eye blinks with techniques like Independent Component Analysis (ICA).(Mcguire, n.d.) Next, elements including time domain statistics, frequency domain characteristics, and time-frequency representations are retrieved from the EEG data, which has been divided into epochs centered around consequential events.(Arsalan et al., 2019) After feature extraction, pertinent features are chosen for additional analysis using dimensionality reduction techniques like principal component analysis (PCA).(Giannakakis et al., 2015) Training and testing sets are made easier by labeling EEG epochs according to experimental circumstances.(Zhang et al., 2020) AUC-ROC, accuracy, precision, recall, and other metrics are measured when machine learning models—which can range from Support Vector Machines to Neural Networks—are chosen, trained on the labeled EEG data, and then assessed using cross-validation procedures.(Agrawal et al., 2021)

Artificial Intelligence

Artificial intelligence computation of EEG data requires advanced processing methods to extract the complex patterns from brain signals. First, preprocessing techniques like filtering are used to concentrate on particular frequency ranges,(Greene et al., 2016) and techniques for removing artifacts like Independent Component Analysis (ICA) guarantee the extraction of real brain signals.(Liu et al., 2016) The EEG data is further standardized by normalization to ensure uniform feature scaling. By dividing the EEG signals into distinct epochs, pertinent temporal events may be isolated, which facilitates the process of feature extraction. The dynamic aspect of brain activity is captured by time-frequency representations, frequency domain features derived from Fourier or wavelet transforms, and time domain statistics combined.(Geetha et al., 2022) Principal component analysis and other dimensionality reduction techniques can be used to simplify the dataset after feature extraction.(Shon et al., 2018)

Image processing

Electroencephalogram signals are converted into visually comprehensible representations during the EEG computation process in image processing, which makes it easier to retrieve relevant data regarding brain activity.(Costin et al., 2012) The first preprocessing processes include filtering to separate out pertinent frequency bands and eliminating artifacts, like those from twitches of the eyes or contractions of the muscles.(Asif et al., 2019) Following processing, these EEG signals are transformed into structures that resemble images and are frequently referred to as spectrograms or time-frequency representations.(Purnamasari & Fernandya, 2019) Electroencephalogram signals are converted into visually comprehensible representations during the EEG computation process in image processing, which makes it easier to retrieve relevant data regarding brain activity.(Parunak et al., 2012) The first preprocessing processes include filtering to separate out pertinent frequency bands and eliminating artifacts, like those from twitches of the eyes or contractions of the muscles. Following processing, these EEG signals are transformed into structures that resemble images and are frequently referred to as spectrograms or time-frequency representations.(Ardila et al., 2016)

Discussion

Examining sleep spindles' traits, purposes, and importance in the context of sleep science and neuroscience constitutes the study and discourse surrounding these entities.Sleep spindles are distinguished by their brief length, lasting just a few seconds, and their frequency, which usually ranges between 11 and 16 hertz. On the electroencephalogram (EEG), they show a greater amplitude than the surrounding brain activity. The central cortex and other parts of the brain are where sleep spindles are most commonly seen. Significance for Neurophysiology :Memory Consolidation: The consolidation of memories is one of the main roles of sleep spindles. It is thought that they help information move from short-term to long-term memory. Sleep Stage: A hallmark of Stage 2 non-rapid eye movement (NREM) sleep are sleep spindles. Although they can happen at any time during the night, they are most common at this period of sleep. Age might bring about changes in sleep spindle properties. In general, as people age, there is a rise in frequency and a fall in amplitude. Sleep Disorders: A number of sleep disorders, including insomnia and several neurological problems, have been related to abnormalities in sleep spindle activity. Sleep spindle monitoring can be used to evaluate the quality of sleep and spot possible sleep-related problems. Cognitive Functions: Research on sleep spindles advances our knowledge of cognitive processes, including memory and learning.

Conclusion:

The use of EEG to analyze sleep spindles offers important new perspectives on the neurophysiological elements of sleep. The electroencephalogram, which documents brain activity, is an essential tool for tracking and comprehending sleep spindles. At the forefront of sleep research, EEG analysis of sleep spindles provides a non-invasive and enlightening way to comprehend the complex dynamics of sleep. Understanding sleep spindles through electroencephalography (EEG) has expanded our understanding of the critical role sleep plays in cognitive and neurological processes, which benefits not only the area of sleep medicine but also the general public.

Bibliography:

1. Al-Salman, W., Li, Y., & Wen, P. (2019). Detecting sleep spindles in EEGs using wavelet fourier https://doi.org/10.1016/j.bspc.2018.10.004
2. Bandarabadi, M., Herrera, C. G., Gent, T. C., Bassetti, C., Schindler, K., & Adamantidis, A. R. (2020). A role for spindles in the onset of rapid eye movement sleep. *Nature Communications*, *11*(1). https://doi.org/10.1038/s41467-020-19076-2
3. Citation Venkata Phanikrishna, B., Pławiak, P. J., & Prakash, A. (2021). *A Brief Review on EEG Signal Pre-processing Techniques for Real-Time Brain-Computer Interface Applications*. 0–16.
4. Clawson, B. C., Durkin, J., & Aton, S. J. (2016). Form and function of sleep spindles across the lifespan. *Neural Plasticity*, *2016*(1). https://doi.org/10.1155/2016/6936381
5. Eltrass, A. S., & Ghanem, N. H. (2023). Investigation of automatic spindle detection in sleep EEG signals contaminated with noise and artifact sources. *Journal of Ambient Intelligence and Humanized Computing*, *14*(9), 12725–12746. https://doi.org/10.1007/s12652-022-04202-3
6. Guttmann-Flury, E., Sheng, X., & Zhu, X. (2023). Channel selection from source localization: A review of four EEG-based brain–computer interfaces paradigms. *Behavior Research Methods*, *55*(4), 1980–2003. https://doi.org/10.3758/s13428-022-01897-2
7. Jaramillo, V., Schoch, S. F., Markovic, A., Kohler, M., Huber, R., Lustenberger, C., & Kurth, S. (2023).

An infant sleep electroencephalographic marker of thalamocortical connectivity predicts behavioral outcome in late infancy. *NeuroImage*, *269*(January). https://doi.org/10.1016/j.neuroimage.2023.119924
8. Kamble, K., & Sengupta, J. (2023). A comprehensive survey on emotion recognition based on electroencephalograph (EEG) signals. *Multimedia Tools and Applications*, *82*(18), 27269–27304. https://doi.org/10.1007/s11042-023-14489-9
9. Lin, C., & Lin, H. (2023). *Rhythms Using HHT*.
10. Lüthi, A. (2014). Sleep spindles: Where they come from, what they do. *Neuroscientist*, *20*(3), 243–256. https://doi.org/10.1177/1073858413500854
11. Mizokuchi, K., Tanaka, T., Sato, T. G., & Shiraki, Y. (2023). Alpha band modulation caused by selective attention to music enables EEG classification. *Cognitive Neurodynamics*, *0123456789*. https://doi.org/10.1007/s11571-023-09955-x
12. Nottage, J. F., Gabay, A., De Meyer, K., Herrik, K. F., Bastlund, J. F., Christensen, S. R., Gijsen, S., & Mehta, M. A. (2023). The effect of ketamine and D-cycloserine on the high frequency resting EEG spectrum in humans. *Psychopharmacology*, *240*(1), 59–75. https://doi.org/10.1007/s00213-022-06272-9
13. Olmez, Y., Koca, G. O., Sengur, A., & Acharya, U. R. (2023). PS-VTS: particle swarm with visit table strategy for automated emotion recognition with EEG signals. *Health Information Science and Systems*, *11*(1), 22. https://doi.org/10.1007/s13755-023-00224-z
14. Pazhoohi, F., Arantes, J., Kingstone, A., & Pinal, D. (2023). Neural Correlates and Perceived Attractiveness of Male and Female Shoulder-to-Hip Ratio in Men and Women: An EEG Study. *Archives of Sexual Behavior*, *52*(5), 2123–2141. https://doi.org/10.1007/s10508-023-02610-w
15. Teplan, M. (2002). FUNDAMENTALS OF EEG MEASUREMENT M . Teplan. *Measurement Science Review*, *2*(Section 2), 1–11. http://www.edumed.org.br/cursos/neurociencia/MethodsEEGMeasurement.pdf
16. Ujma, P. P., Bódizs, R., Gombos, F., Stintzing, J., Konrad, B. N., Genzel, L., Steiger, A., & Dresler, M. (2015). Nap sleep spindle correlates of intelligence. *Scientific Reports*, *5*, 1–8. https://doi.org/10.1038/srep17159
17. Wei, L., Ventura, S., Ryan, M. A., Mathieson, S., Boylan, G. B., Lowery, M., & Mooney, C. (2022). Deep-spindle: An automated sleep spindle detection system for analysis of infant sleep spindles. *Computers in Biology and Medicine*, *150*(September), 106096. https://doi.org/10.1016/j.compbiomed.2022.106096
18. Wu, C. H., De Doncker, W., & Kuppuswamy, A. (2023). Electroencephalography-Derived Functional Connectivity in Sensorimotor Networks in Post Stroke Fatigue. *Brain Topography*, *36*(5), 727–735. https://doi.org/10.1007/s10548-023-00975-8
19. Yuan, I., Chao, J. Y., Kurth, C. D., Missett, R., & Cornelissen, L. (2023). Intraoperative EEG Monitoring in Pediatric Anesthesia. *Current Anesthesiology Reports*, *13*(3), 135–142. https://doi.org/10.1007/s40140-023-00562-4
20. Abo-Zahhad, M., Ahmed, S. M., & Abbas, S. N. (2015a). A New EEG Acquisition Protocol for Biometric Identification Using Eye Blinking Signals. *International Journal of Intelligent Systems and Applications*, *7*(6), 48–54. https://doi.org/10.5815/ijisa.2015.06.05
21. Abo-Zahhad, M., Ahmed, S. M., & Abbas, S. N. (2015b). A novel biometric approach for human identification and verification using eye blinking signal. *IEEE Signal Processing Letters*, *22*(7), 876–

880. https://doi.org/10.1109/LSP.2014.2374338
22. Agrawal, J., Gupta, M., & Garg, H. (2021). Early Stress Detection and Analysis using EEG signals in Machine Learning Framework. *IOP Conference Series: Materials Science and Engineering*, *1116*(1), 012134. https://doi.org/10.1088/1757-899x/1116/1/012134
23. Ahammed, K., & Ahmed, M. U. (2020). QUANTIFICATION of MENTAL STRESS USING COMPLEXITY ANALYSIS of EEG SIGNALS. *Biomedical Engineering - Applications, Basis and Communications*, *32*(2), 1–7. https://doi.org/10.4015/S1016237220500118
24. Ardila, A., Bernal, B., & Rosselli, M. (2016). How Localized are Language Brain Areas? A Review of Brodmann Areas Involvement in Oral Language. *Archives of Clinical Neuropsychology*, *31*(1), 112–122. https://doi.org/10.1093/arclin/acv081
25. Arsalan, A., Majid, M., Butt, A. R., & Anwar, S. M. (2019). Classification of Perceived Mental Stress Using A Commercially Available EEG Headband. *IEEE Journal of Biomedical and Health Informatics*, *23*(6), 2257–2264. https://doi.org/10.1109/JBHI.2019.2926407
26. Asif, A., Majid, M., & Anwar, S. M. (2019). Human stress classification using EEG signals in response to music tracks. *Computers in Biology and Medicine*, *107*(August 2018), 182–196. https://doi.org/10.1016/j.compbiomed.2019.02.015
27. Chambayil, B., Singla, R., & Jha, R. (2010). EEG eye blink classification using neural network. *WCE 2010 - World Congress on Engineering 2010*, *1*(June), 63–66.
28. Costin, R., Rotariu, C., & Pasarica, A. (2012). Mental stress detection using heart rate variability and morphologic variability of EeG signals. *EPE 2012 - Proceedings of the 2012 International Conference and Exposition on Electrical and Power Engineering*, *Epe*, 591–596. https://doi.org/10.1109/ICEPE.2012.6463870
29. Geetha, A., Bharathi, S. S., Bernard, A. R., Teja, R. Y., & Pradeep, K. (2022). Emotional Recognition System Using EEG and Psycho Physiological Signals. *Lecture Notes in Networks and Systems*, *356*, 327–335. https://doi.org/10.1007/978-981-16-7952-0_30
30. Giannakakis, G., Grigoriadis, D., & Tsiknakis, M. (2015). Detection of stress/anxiety state from EEG features during video watching. *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, *2015-November*, 6034–6037. https://doi.org/10.1109/EMBC.2015.7319767
31. Glisson, W. B., & Chowdhury, G. G. (2002). Design of a digital dissertation information management system. *Program*, *36*(3), 152–165. https://doi.org/10.1108/00330330210440449
32. Greene, S., Thapliyal, H., & Caban-Holt, A. (2016). A Survey of Affective Computing for Stress Detection. *IEEE Consumer Electronics Magazine*, *5*(October), 44–56.
33. Haak, M., Bos, S., Panic, S., & Rothkrantz, L. J. M. (2009). Detecting stress using eye blinks during game playing. *10th International Conference on Intelligent Games and Simulation, GAME-ON 2009*, *January*, 75–82.
34. Ihc, F., Deshmukh, M. D., & Kamble, S. (2013). *International Journal of Advanced Research in Survey on Hierarchical Document Clustering Techniques*. *3*(7), 157–161.
35. Ishimaru, S., Kunze, K., Kise, K., Weppner, J., Dengel, A., Lukowicz, P., & Bulling, A. (2014). In the blink of an eye - Combining head motion and eye blink frequency for activity recognition with google glass. *ACM International Conference Proceeding Series*. https://doi.org/10.1145/2582051.2582066
36. Iwasaki, M., Kellinghaus, C., Alexopoulos, A. V., Burgess, R. C., Kumar, A. N., Han, Y. H., Lüders, H. O., & Leigh, R. J. (2005). Effects of eyelid closure, blinks, and eye movements on the

electroencephalogram. *Clinical Neurophysiology*, *116*(4), 878–885. https://doi.org/10.1016/j.clinph.2004.11.001
37. Jebelli, H., Hwang, S., & Lee, S. (2018). EEG Signal-Processing Framework to Obtain High-Quality Brain Waves from an Off-the-Shelf Wearable EEG Device. *Journal of Computing in Civil Engineering*, *32*(1). https://doi.org/10.1061/(asce)cp.1943-5487.0000719
38. Khosla, A., Khandnor, P., & Chand, T. (2020). A comparative analysis of signal processing and classification methods for different applications based on EEG signals. *Biocybernetics and Biomedical Engineering*, *40*(2), 649–690. https://doi.org/10.1016/j.bbe.2020.02.002
39. Li, R., & Principe, J. C. (2006). Blinking artifact removal in cognitive EEG data using ICA. *Annual International Conference of the IEEE Engineering in Medicine and Biology - Proceedings*, *3*, 5273–5276. https://doi.org/10.1109/IEMBS.2006.260605
40. Liu, J., Meng, H., Nandi, A., & Li, M. (2016). Emotion detection from EEG recordings. *2016 12th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery, ICNC-FSKD 2016*, 1722–1727. https://doi.org/10.1109/FSKD.2016.7603437
41. Mannan, M. M. N., Kim, S., Jeong, M. Y., & Kamran, M. A. (2016). Hybrid EEG--Eye Tracker: Automatic Identification and Removal of Eye Movement and Blink Artifacts from Electroencephalographic Signal. *Sensors (Basel, Switzerland)*, *16*(2), 241. https://doi.org/10.3390/s16020241
42. Manoilov, P. (2007). Eye-blinking Artefacts analysis. *ACM International Conference Proceeding Series*, *285*, 1–6. https://doi.org/10.1145/1330598.1330654
43. McFarland, D. J., Todd Lefkowicz, A., & Wolpaw, J. R. (1997). Design and operation of an EEG-based brain-computer interface with digital signal processing technology. *Behavior Research Methods, Instruments, and Computers*, *29*(3), 337–345. https://doi.org/10.3758/BF03200585
44. Mcguire, D. (n.d.). *Computational Biology Modeling and Analysis*.
45. Motamedi-Fakhr, S., Moshrefi-Torbati, M., Hill, M., Hill, C. M., & White, P. R. (2014). Signal processing techniques applied to human sleep EEG signals - A review. *Biomedical Signal Processing and Control*, *10*(1), 21–33. https://doi.org/10.1016/j.bspc.2013.12.003
46. Nunez, P., Nunez, M., & Srinivasan, R. (2016). *Chapter 7 Electroencephalography (EEG): Neurophysics, experimental methods, and signal processing*. https://doi.org/10.13140/rg.2.2.12706.63687
47. Parunak, H. V. D., Brooks, S. H., Brueckner, S., & Gupta, R. (2012). Apoptotic stigmergic agents for real-time swarming simulation. *AAAI Fall Symposium - Technical Report*, *FS-12-04*, 59–64.
48. Peng, H., Hu, B., Zheng, F., Fan, D., Zhao, W., Chen, X., Yang, Y., & Cai, Q. (2013). A method of identifying chronic stress by EEG. *Personal and Ubiquitous Computing*, *17*(7), 1341–1347. https://doi.org/10.1007/s00779-012-0593-3
49. Purnamasari, P. D., & Fernandya, A. (2019). Real time EEG-based stress detection and meditation application with K-nearest neighbor. *IEEE Region 10 Humanitarian Technology Conference, R10-HTC*, *2019-November*, 49–54. https://doi.org/10.1109/R10-HTC47129.2019.9042488
50. Rampil, I. J. (1998). A primer for EEG signal processing in anesthesia. *Anesthesiology*, *89*(4), 980–1002. https://doi.org/10.1097/00000542-199810000-00023
51. Roy, A., Baxter, B., & He, B. (2014). High-definition transcranial direct current stimulation induces both acute and persistent changes in broadband cortical synchronization: A simultaneous tDCS-EEG study. *IEEE Transactions on Biomedical Engineering*, *61*(7), 1967–1978.

https://doi.org/10.1109/TBME.2014.2311071

52. Roy, R. N., Charbonnier, S., & Bonnet, S. (2014). Eye blink characterization from frontal EEG electrodes using source separation and pattern recognition algorithms. *Biomedical Signal Processing and Control*, *14*, 256–264. https://doi.org/10.1016/j.bspc.2014.08.007
53. Schalk, G., Mellinger, J., & Roman-Gonzalez, A. (2010). EEG Signal Processing for BCI Applications Avid Roman-Gonzalez To cite this version : ... *Practical Guide to Brain–Computer Interfacing with …*, 9–36. http://link.springer.com/chapter/10.1007/978-1-84996-092-2_2
54. Shon, D., Im, K., Park, J. H., Lim, D. S., Jang, B., & Kim, J. M. (2018). Emotional stress state detection using genetic algorithm-based feature selection on EEG signals. *International Journal of Environmental Research and Public Health*, *15*(11). https://doi.org/10.3390/ijerph15112461
55. Singla, R., Chambayil, B., Khosla, A., & Santosh, J. (2011). Comparison of SVM and ANN for classification of eye events in EEG. *Journal of Biomedical Science and Engineering*, *04*(01), 62–69. https://doi.org/10.4236/jbise.2011.41008
56. Tyagi, A. (2012). A Review of Eeg Sensors used for Data Acquisition. *Electronics and Instrumentation*, *Ncfaaiia*, 13–18.
57. Wang, J., Cao, J., Hu, D., Jiang, T., & Gao, F. (2021). Eye Blink Artifact Detection with Novel Optimized Multi-Dimensional Electroencephalogram Features. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *29*, 1494–1503. https://doi.org/10.1109/TNSRE.2021.3099232
58. Zhang, Y., Wang, Q., Chin, Z. Y., & Keng Ang, K. (2020). Investigating different stress-relief methods using Electroencephalogram (EEG). *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, *2020-July*, 2999–3002. https://doi.org/10.1109/EMBC44109.2020.9175900