Identification of working memory status in children from EEG signal features using discrete wavelet transform

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ABSTRACT

The conventional method for assessing the working memory performance of children is time-consuming and potentially inaccurate, especially when dealing with many samples. Therefore, an automated system that can produce swift and accurate results is required. Electroencephalograms (EEG) can be used to analyse the working memory status of children by extracting specific features from the EEG signal, which can be incorporated into an automatic system to reduce manpower and processing time for analysis. This project used EEG recording to identify children's working memory status while they were performing working memory tasks. EEG signals were acquired from both children and adults using an automated computer-based working memory assessment tool, processed, and analyzed. The discrete wavelet transform (DWT) was then employed to identify five distinct working memory statuses: distracted, confused, daydreaming, losing focus, and active. DWT was also used to extract features that demonstrate these various statuses. The results showed that DWT could accurately identify the working memory status of both children and adults from their EEGs. This work has thus provided a more efficient method for extracting features from EEG signals to identify working memory statuses in both children and adults.

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1. INTRODUCTION

Working memory (WM) is a cognitive system that allows the temporary storage and manipulation of information [1], [2]. It is the "mental workbench" of the brain and is responsible for holding onto, organizing, and manipulating information to complete a task. WM is limited in capacity, so it is important that the working memory is trained to focus on relevant details and ignore irrelevant ones to maximize its effectiveness. WM plays an important role in many cognitive processes such as language comprehension, learning new skills, and problem solving. Therefore, it is important to diagnose WM issues in children early, as the diagnosis can be used to identify and correct learning issues related to it.

WM is composed of three primary components: the phonological loop, the visuospatial sketchpad, and the central executive. The phonological loop stores verbal information, such as sounds or words, using subvocal rehearsal. The visuospatial sketchpad stores visual and spatial information such as shapes or directions. Finally, the central executive oversees all activities of working memory as well as tasks like planning, problem solving, and decision making. Subsequently, these components have been discovered to help with visual, writing and listening tasks [3]. Visual WM utilizes visual cues to process information, for instance, visual WM store information from images and other types of visual data. In contrast, writing WM is accessed by recollecting words that have been previously written down. Finally, listening WM is accessed when listening tasks are involved. This was demonstrated in a study by [1] regarding children's WM assessment.

Electroencephalograms (EEG) is a non-invasive technique used to measure electrical activity in the brain. It involves attaching electrodes to certain areas of the scalp to detect electrical activity of neurons within the brain. The acquired signals are then amplified, filtered, and recorded as an EEG trace. This trace can be used to investigate various aspects of brain function such as sleep stages [4], seizure focus [5]-[7], and the effect of drugs [8], [9] or other stimuli. Additionally, EEG is an important tool for diagnosing neurological disorders [10] and monitoring brain function to understand how the brain works. Moreover, it is used to discover a type of illness of the brain such as a tumor, or discover the mental state of the subject, such as anxiety, stress, schizophrenia [11] or panic [10]. The normal EEG spectrum consists of the following five bands: gamma, beta, alpha, theta, and delta [12]. These bands represent different levels of neural activity. The activity of each frequency band is associated with a particular mental state, and the ratio between different frequency bands can be used to differentiate between different mental states.

The importance of understanding WM performance of the brain is to ascertain its capacity for absorbing and processing information. There are several methods for evaluating working memory, such as hands-on paper tests [1] or EEG signal analysis [13]-[17]. The hands-on test method evaluates WM performance through a set of multiple questions [1]. This method is time-intensive, as recording scores for a large sample size requires a significant amount of effort and may not yield accurate results. Additionally, the researcher does not consider the analysis of the children's neurological characteristics.

The EEG analysis method is more advanced, wherein the subject's EEG is measured while they are performing WM-specific tasks. Performance is based on features extracted from the EEG signal [18]. Tumari *et al*. [13], researchers utilized EEG to identify WM impairments in children using wavelet analysis. The experiments studied the mean frequency of EEG electrodes placed at F3, F4, F7, and F8 locations when the subject was tasked with three WM-related tasks (visual memory, visual patterns, and mathematical questions).

Discrete wavelet transform (DWT) has been widely used to extract features from EEG signals [19]. DWT is a powerful mathematical tool employed for signal analysis in various data types like images and audio [20], [21]. Its principle involves breaking down signals into smaller components known as wavelets. The DWT uses wavelets, which have localized support in both the time and scale domains. This property makes the DWT especially adept at representing signals with localized features, such as sharp edges in images or abrupt changes in audio signals. With its wide-ranging capabilities, the DWT has become a vital tool in diverse fields such as image and signal processing, data analysis, and machine learning [22]-[25].

In this paper, we measure and analyze EEG signals collected from children and adult subjects when performing WM-related tasks, extract features using fast fourier transform (FFT), power spectral density (PSD), and DWT. A comparison of EEG signal features and game scores was conducted to identify their relationship. The subject's mental state was then determined to ascertain the WM status of the subjects. The analysis highlighted distinct features between children and adults, providing insights into how cognitive processes vary during WM tasks. These findings demonstrate how specific EEG signal features correspond to different mental states.

2. METHOD

2.1. Experiment overview

The methodology began with EEG signal acquisition, and preprocessing and extraction of the respective EEG bands. Feature extraction from the bands was performed using FFT, PSD, and DWT, as shown in Figure 1. The signals from those electrodes were then filtered to remove noise. This is because EEG recordings are especially susceptible to noise from a variety of sources. These may include interference from power cables, poor electrode contact, movement artifacts, and physiological noise. EEG sources can also be affected by environmental noise sources such electromagnetic fields created by fluorescent lighting, air conditioning, computers, and other electrical equipment. Noise from biological activities may also be present noise from cardiac sources, muscle activity, and eye movements. Subsequently, FFT and PSD were computed. Finally, DWT was used to extract features from the transformed signal.

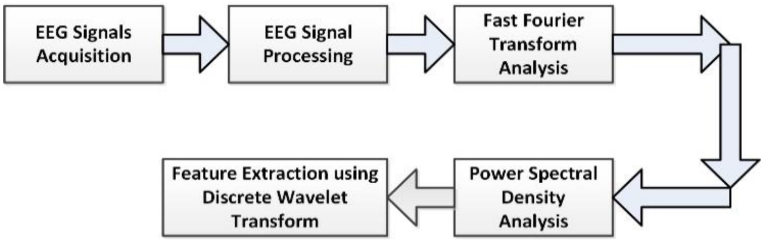

Figure 1. Process of extracting features from EEG signals with working memory status information

2.2. Games for working memory assessment

Each subject was asked to play two games, namely the Dot Game and the Shape Game. A 2-minute resting period was given after the subjects played both games. The Dot Game is like a commonly known children game called "Simon Says" [26], in which the subject must remember and recall the arrangement of a sequence of dot patterns (Figure 2(a)). The game has nine levels, where the number of levels is equal to the number of dot sequences that the subject needs to remember.

The Shape Game is like the Dot Game, except it displays shapes as a pattern for the subject to remember, and with the addition of inter-stimulus questions, as shown in Figure 2(b). The inter-stimulus question asks the subject to remember the shape that appeared in Figure 2(b) and asks the subject whether the shape that appeared in Figure 2(c) is identical to the shape shown in Figure 2(c). Moreover, the subject needs to remember all the shapes in sequence with the inter-stimulus distraction.

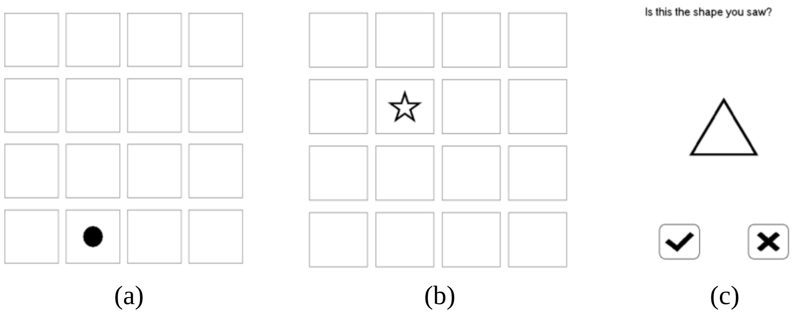

Figure 2. Samples of game used in the assessment: (a) dot task, (b) shape task, and (c) inter stimulus question

2.3. Electroencephalograms acquisition

Ten subjects were tested with five adults and five children. The adult subjects were between 23 and 24 years old, while the child subjects were aged between eight to twelve years old. The Enorbio, a neuroelectric EEG device with 32 electrodes and NIC 2.0 software was used to record its EEG signal. The electrodes used for the analysis were all channels located in the frontal lobe of the brain, which are Fp1, F7, F3, FZ, and Fp2. These electrodes were selected since they are associated with working memory [27]-[29]. The Fp1 electrode records the visual WM and verbal retrieval parts of the brain. Electrode F7 recorded visual and auditory working memory activities, capturing both what the subject sees and hears. Electrode F3 recorded the decision and planning part of the brain that decides whether the answer to the question is right or wrong. Electrode Fp2 recorded the episodic memory part of the brain, which was used to recall past events that gather information to process and answer the questions given. Electrode Fz represents the focus part of the brain, where it gathers information from both the left and right frontal lobes and sends action signals to other parts of the brain. The EEG channels underwent FFT and PSD analysis to examine the signal frequency and evaluate the strength of the signal.

2.4. Noise removal and feature extraction

The signals were filtered using a high-pass Butterworth filter set with a cut-off frequency of 0.6 Hz to remove the baseline drift. After the baseline drift was removed, the EEG signal was then filtered with several bandpass filters to separate the signal into the EEG frequency bands. The frequency and power characteristics of the signals were observed using FFT and PSD, respectively. Finally, the signal frequency bands were processed using DWT with Daubechies order 4 (db4) as mother wavelet to separate the signal into multiple scales for feature extraction, as shown in Figure 3. Regularity is a very important criterion in selecting a wavelet. With db4, the discontinuity is well detected. The advantage of regularity is useful for getting nice features such as a smooth reconstructed signal.

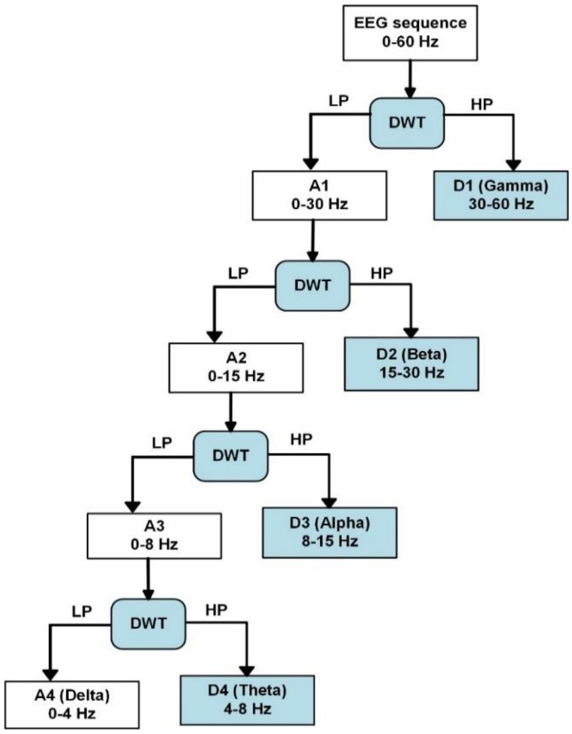

Figure 3. Sub-band of decomposition level with a frequency range

Finally, (1) was used to find the ratio between the beta energy band (E_{β}), over the summation of theta (E_{Θ}), alpha (E_{α}), and delta (E_{δ}), energy bands (commonly called the F-ratio) (1). EEG energy bands measure different frequencies of brain waves and can be used to diagnose various neurological disorders, determine sleep patterns, and evaluate emotional states. The four main EEG energy bands are delta, theta, alpha, and beta. Delta waves are the slowest with a frequency range of 0-4 Hz and represent deep sleep. Theta waves have a frequency range of 4-8 Hz and are associated with drowsiness and dreaming. Alpha waves have a frequency range of 8-13 Hz and represent a relaxed alert state. Beta waves have a frequency range of 13-30 Hz and indicate an active mental state. Delta is the dominant wave during deep sleep but can also appear during intense emotions or daydreaming. Theta can occur during light sleep or moments of creativity as well as times when we're distracted or unfocused. Alpha is the most seen wave during wakefulness, especially when the person is relaxed but still alert. Beta is seen during times of concentration or physical activity, when there is more input from external sources such as sight, sound, and smell.

$$F = \frac{E_{\beta}}{E_{\alpha}+E_{\theta}+E_{\delta}} \quad (1)$$

The formula of the F value is the ratio of the mind in a working state as a beta-band wave with the mind in a relaxed state that is a summation of the alpha, theta, and delta-band wave shown in (1). Another method to represent (1) is with (2), where the summation of beta is divided by all the summation of alpha, theta, and delta. Furthermore, (3) is an equation for the power band that uses for the ratio of theta power and beta power. This equation is used to detect daydreaming status when the value reaches 3 or above [30].

$$F = \frac{\sum_k (d_{\beta}(k))^2}{\sum_k (d_{\alpha}(k))^2 + \sum_k (d_{\theta}(k))^2 + \sum_k (d_{\delta}(k))^2} \quad (2)$$

$$Power = \sum \frac{x^2}{L(x)} \quad (3)$$

3. RESULTS AND DISCUSSION

3.1. Extracted features

Tables 1 and 2 show the features, which are F value, beta band power, and theta/beta extracted from EEG signals of children and adults, respectively. Note that the minimum and maximum F values of children's EEGs are smaller than those of adults' EEGs. However, the range of the beta power of children's EEG is higher than that of adults. The children also have greater theta/beta power compared to adults. There is a relationship between the F value, beta band power, and theta/beta observed from most adults' EEG features. In all channels (Fp1, F7, F3, Fp2, and Fz) for three subjects, when F value decreases (from task 1 to task 2), the beta band power and theta/beta increase, and vice versa. The same relationship is observed in four children's EEG features on specific channels.

Table 1. Game scores and features of children's EEG

Subject	Score (T1)	Score (T2)	Channel	F (T1)	F(T2)	Beta (T1)	Beta (T2)	T/B (T1)	T/B (T2)
6	5	2	Fp1	0.1650	0.1132	2249.9	17038.7	0.1101	0.0541
			F7	0.2041	0.1797	9557.61	19026.8	0.0275	0.0293
			F3	0.0434	0.0427	15080.1	7895.15	0.7853	0.5671
			Fp2	0.1866	0.1545	33072.9	18033.2	0.0730	0.0362
			Fz	0.1929	0.1799	29998.4	17724.3	0.0358	0.0298
7	7	8	Fp1	0.0976	0.0861	22564.6	55225.3	0.5330	0.4389
			F7	0.2069	0.2149	39660.3	83809.1	0.0587	0.0517
			F3	0.1197	0.1335	24824.7	63637.2	0.3469	0.2505
			Fp2	0.0762	0.0456	17368.5	41223.6	1.4287	1.6425
			Fz	0.1473	0.1602	29402.1	68882.6	0.2142	0.1578
8	6	9	Fp1	0.0366	0.0265	10960.6	47518	1.4305	1.3778
			F7	0.0859	0.8840	7301.28	16304.6	0.7745	0.7156
			F3	0.0659	0.0661	17646.7	62063.7	0.8574	0.7070
			Fp2	0.0353	0.0305	15460.3	33409.8	1.8536	1.4457
			Fz	0.1300	0.1697	32699.5	114792	0.2081	0.1010
9	8	6	Fp1	00251	0.0310	4958.33	290.86	2.9972	28.188
			F7	0.0407	0.0031	1850.5	284.87	2.7074	28.234
			F3	0.0374	0.0029	7495.8	280.74	1.7292	29.592
			Fp2	0.0135	0.0029	289.6	289.69	5.7995	29.477
			Fz	0.0186	0.0029	10180.9	262.26	2.3179	30.253
10	6	6	Fp1	0.0429	0.0066	9649.4	339.91	2.3915	21.468
			F7	0.0612	0.0064	7557.6	316.36	1.0218	22.395
			F3	0.0828	0.0080	18012	368.02	0.5018	18.011
			Fp2	0.0978	0.0131	24537	620.29	0.2677	10.345
			Fz	0.0346	0.0055	11575.7	247.01	1.0311	26.102

3.2. Relationship between game score and the feature

By comparing the game score, F value, beta power, and theta/beta power for both task 1 and task 2 shown in Tables 1 and 2, a relationship between the game score and the features can be obtained. Note that the subject is given 1 mark for every level they completed. For example, if the subject reaches level 5 then the subject's score is 5. Among all ten subjects, five statuses were identified: distracted on subject 1, daydreaming on subjects 2, 9, and 10, confusion on subjects 3 and 6, losing focus on subjects 4 and 5, and active status on subjects 7 and 8.

The distracted state occurred when the F value and theta/beta ratio increased while the beta band power and score from task 1 to task 2 decreased. Because theta/beta is increasing and beta is decreasing, the subject is relaxed, but the brain is not tired, indicating the subject was distracted, resulting in a low task 2 score. Daydreaming occurred in three subjects when the F value and beta power decreased but the theta/beta power increased [9]. This indicates that the subjects are tired, and because they have very high theta/beta power and low beta power, the subjects are not focused. However, based on the results of the subject with the daydreaming status, they manage to score well on both tasks 1 and 2. This demonstrates that the daydreamer has no difficulty completing the visual activity tasks.

When all features and scores are decreasing, confusion occurs. This occurred when the subjects were tired and both beta and theta were low, causing the brain to fail to understand the instruction and thus failing to score the task highly. When beta and theta/beta power increase, but the F value and score decrease, this is referred to as losing focus. The status only indicates that the subjects are tired, resulting in a slightly lower score for the subject with a high beta power value. Finally, the active status occurs when the F value, beta power, and score increase while the theta/beta power decreases. This indicates that the subjects have no difficulty performing both tasks.

Table 2. Game score and features of adults' EEG

Subject	Score (T1)	Score (T2)	Channel	F (T1)	F(T2)	Beta (T1)	Beta (T2)	T/B (T1)	T/B (T2)
1	6	2	Fp1	0.0119	0.0208	21542.5	7859.1	0.8120	0.8117
			F7	0.0744	0.1097	33528.2	11363.8	0.2499	0.2429
			F3	0.1237	0.1430	36737.4	11909.8	0.2152	0.2222
			Fp2	0.0052	0.0051	4336.4	1349.2	15.40	16.159
			Fz	0.0536	0.0674	23854.2	8054.34	0.6765	0.7203
2	8	6	Fp1	0.080	0.0199	29789.6	773.54	0.2342	12.519
			F7	0.1027	0.0178	10422.6	693.44	0.8779	14.370
			F3	0.1328	0.0205	6023.91	793.26	0.3841	12.448
			Fp2	0.0411	0.0181	30877.3	743.74	0.3633	13.695
			Fz	0.0931	0.0181	28803.4	649.98	0.4916	14.183
3	8	2	Fp1	0.0316	0.0264	1103.44	691.76	2.1894	0.3175
			F7	0.0424	0.1019	947.52	557.42	2.568	0.325
			F3	0.0762	0.1867	3358.99	10114.9	0.9815	0.050
			Fp2	0.0280	0.0173	437.03	110.87	3.9298	0.9075
			Fz	0.2280	0.0399	71671.7	180.68	0.0068	0.9647
4	4	5	Fp1	0.0785	0.0585	30608.5	46976.8	0.0452	0.0661
			F7	0.1365	0.1009	22896.3	23654.8	0.1529	0.2705
			F3	0.0741	0.0796	17749.4	15515	0.3717	0.3573
			Fp2	0.0476	0.0397	24541.7	40238	0.1005	0.1267
			Fz	0.0265	0.0271	11370.5	21008.6	1.0665	1.0156
5	9	8	Fp1	0.1793	0.1389	46818.4	52605.5	0.3692	0.6744
			F7	0.2313	0.2224	78753.2	106690	0.0290	0.0540
			F3	0.1608	0.1379	39447.4	50237.5	0.5165	0.6925
			Fp2	0.1896	0.1536	57101.8	65140.5	0.2000	0.3660
			Fz	0.0698	0.0624	31694	42085.8	0.9735	0.9984

4. CONCLUSION

This work focused on the feature extraction of EEG signals from children and adults using DWT and the identification of the memory states based on the extracted features. Three features; F value, beta band power, and theta/beta were extracted from DWT, and five memory states were identified; distraction, daydreaming, confusion, losing focus, and active. Furthermore, the relationship between the features, game score and memory states were discovered. The analysis revealed that an increase in F value and theta/beta ratio, alongside a decrease in beta band power and score, indicates distraction. A decrease in F value and beta power, combined with an increase in the theta/beta ratio, suggests daydreaming. Confusion is marked by a reduction in all features and the score. Losing focus is indicated by an increase in beta and theta/beta power, while the F value and score decrease. Active status is observed when the F value, beta power, and score increase, while the theta/beta ratio decreases. The results demonstrate that DWT could be used to determine the memory states through the extracted features. This work provides an efficient method of assessing the working memory status of the children and adults from the EEG signals.

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REFERENCES

[1] K. Cabbage *et al.*, "Assessing Working Memory in Children: The Comprehensive Assessment Battery for Children-Working Memory (CABC-WM)," *Journal of Visualized Experiments*, no. 124, Jun. 2017, doi: 10.3791/55121.

[2] Y. Zhao, S. Kuai, T. P. Zanto, and Y. Ku, "Neural Correlates Underlying the Precision of Visual Working Memory," *Neuroscience*, vol. 425, pp. 301–311, Jan. 2020, doi: 10.1016/j.neuroscience.2019.11.037.

[3] D. Tomasi, T. Ernst, E. C. Caparelli, and L. Chang, "Common deactivation patterns during working memory and visual attention tasks: An intra-subject fMRI study at 4 Tesla," *Human Brain Mapping*, vol. 27, no. 8, pp. 694–705, Jan. 2006, doi: 10.1002/hbm.20211.

[4] W. Al-Salman, Y. Li, A. Y. Oudah, and S. Almaged, "Sleep stage classification in EEG signals using the clustering approach based probability distribution features coupled with classification algorithms," *Neuroscience Research*, vol. 188, pp. 51–67, Mar. 2023, doi: 10.1016/j.neures.2022.09.009.

[5] X. Wang, Y. Wang, D. Liu, Y. Wang, and Z. Wang, "Automated recognition of epilepsy from EEG signals using a combining

space–time algorithm of CNN-LSTM," *Scientific Reports*, vol. 13, no. 1, Sep. 2023, doi: 10.1038/s41598-023-41537-z.
[6] N. S. Tawfik, S. M. Youssef, and M. Kholief, "A hybrid automated detection of epileptic seizures in EEG records," *Computers & Electrical Engineering*, vol. 53, pp. 177–190, Jul. 2016, doi: 10.1016/j.compeleceng.2015.09.001.
[7] I. B. Slimen, L. Boubchir, Z. Mbarki, and H. Seddik, "EEG epileptic seizure detection and classification based on dual-tree complex wavelet transform and machine learning algorithms," *The Journal of Biomedical Research*, vol. 34, no. 3, p. 151, 2020, doi: 10.7555/jbr.34.20190026.
[8] C. Limotai, N. Phayaph, B. Pattanasilp, J. Mokklaew, and N. Limotai, "Effects of antiepileptic drugs on electroencephalography (EEG): Insights and applicability," *Epilepsy & Behavior*, vol. 110, p. 107161, Sep. 2020, doi: 10.1016/j.yebeh.2020.107161.
[9] G. A. Balanza *et al.*, "An electroencephalogram biomarker of fentanyl drug effects," *PNAS Nexus*, vol. 1, no. 4, Aug. 2022, doi: 10.1093/pnasnexus/pgac158.
[10] M. Aljalal, S. A. Aldosari, M. Molinas, K. AlSharabi, and F. A. Alturki, "Detection of Parkinson's disease from EEG signals using discrete wavelet transform, different entropy measures, and machine learning techniques," *Scientific Reports*, vol. 12, no. 1, Dec. 2022, doi: 10.1038/s41598-022-26644-7.
[11] B. Gosala, P. Dindayal Kapgate, P. Jain, R. Nath Chaurasia, and M. Gupta, "Wavelet transforms for feature engineering in EEG data processing: An application on Schizophrenia," *Biomedical Signal Processing and Control*, vol. 85, p. 104811, Aug. 2023, doi: 10.1016/j.bspc.2023.104811.
[12] A. Khosla, P. Khandnor, and T. Chand, "A comparative analysis of signal processing and classification methods for different applications based on EEG signals," *Biocybernetics and Biomedical Engineering*, vol. 40, no. 2, pp. 649–690, Apr. 2020, doi: 10.1016/j.bbe.2020.02.002.
[13] S. Z. M. Tumari, R. Sudirman, and A. H. Ahmad, "Identification of working memory impairments in normal children using wavelet approach," in *2012 IEEE Symposium on Industrial Electronics and Applications*, IEEE, Sep. 2012, pp. 326–330, doi: 10.1109/isiea.2012.6496653.
[14] E. T. Aronen, V. Vuontela, M.-R. Steenari, J. Salmi, and S. Carlson, "Working memory, psychiatric symptoms, and academic performance at school," *Neurobiology of Learning and Memory*, vol. 83, no. 1, pp. 33–42, Jan. 2005, doi: 10.1016/j.nlm.2004.06.010.
[15] M. A. Bell and K. Cuevas, "Using EEG to Study Cognitive Development: Issues and Practices," *Journal of Cognition and Development*, vol. 13, no. 3, pp. 281–294, Jul. 2012, doi: 10.1080/15248372.2012.691143.
[16] J. O. Rinne *et al.*, "The translating brain: cerebral activation patterns during simultaneous interpreting," *Neuroscience Letters*, vol. 294, no. 2, pp. 85–88, Nov. 2000, doi: 10.1016/s0304-3940(00)01540-8.
[17] M. S. S. Sulaiman, W. Mansor, and K. Cengiz, "Identification of Nicotine Effect on Working Memory via Electroencephalogram," *International Journal of Advanced Trends in Computer Science and Engineering*, vol. 9, no. 1.4, pp. 244–248, Sep. 2020, doi: 10.30534/ijatcse/2020/3691.42020.
[18] I. Stancin, M. Cifrek, and A. Jovic, "A Review of EEG Signal Features and Their Application in Driver Drowsiness Detection Systems," *Sensors*, vol. 21, no. 11, p. 3786, May 2021, doi: 10.3390/s21113786.
[19] F. Sherwani, S. Shanta, B. S. K. K. Ibrahim, and M. S. Huq, "Wavelet based feature extraction for classification of motor imagery signals," in *2016 IEEE EMBS Conference on Biomedical Engineering and Sciences (IECBES)*, IEEE, Dec. 2016, pp. 360–364, doi: 10.1109/iecbes.2016.7843474.
[20] M. Akin, "Identification of Nicotine Effect on Working Memory via Electroencephalogram," *International Journal of Advanced Trends in Computer Science and Engineering*, vol. 9, no. 1.4, pp. 244–248, Sep. 2020, doi: 10.30534/ijatcse/2020/3691.42020.
[21] M. ur Rehman and R. A. Khan, "The Legendre wavelet method for solving fractional differential equations," *Communications in Nonlinear Science and Numerical Simulation*, vol. 16, no. 11, pp. 4163–4173, Nov. 2011, doi: 10.1016/j.cnsns.2011.01.014.
[22] N. Ye, Y. Sun, and J. Yang, "EEG based fatigue driving detection using wavelet packet sub-band energy ratio," in *The 27th Chinese Control and Decision Conference (2015 CCDC)*, IEEE, May 2015, pp. 3669–3672, doi: 10.1109/ccdc.2015.7162562.
[23] P. Zarjam, J. Epps, F. Chen, and N. H. Lovell, "Classification of Working Memory Load Using Wavelet Complexity Features of EEG Signals," in *Neural Information Processing*, Springer Berlin Heidelberg, 2012, pp. 692–699, doi: 10.1007/978-3-642-34481-7_84.
[24] S. Zahirovic *et al.*, "Wavelet Transform as a Helping Tool During Eeg Analysis in Children with Epilepsy," *Acta Informatica Medica*, vol. 29, no. 2, p. 104, 2021, doi: 10.5455/aim.2021.29.104-107.
[25] S. N. S. S. Daud and R. Sudirman, "Wavelet Based Filters for Artifact Elimination in Electroencephalography Signal: A Review," *Annals of Biomedical Engineering*, vol. 50, no. 10, pp. 1271–1291, Aug. 2022, doi: 10.1007/s10439-022-03053-5.
[26] K. A. Chalmers and E. E. Freeman, "Working Memory Power Test for Children," *Journal of Psychoeducational Assessment*, vol. 37, no. 1, pp. 105–111, Sep. 2017, doi: 10.1177/0734282917731458.
[27] S. Z. M. Tumari and R. Sudirman, "Classification of Working Memory Impairment in Children Using Electroencephalograph Signal at the Prefrontal Cortex," in *2014 2nd International Conference on Artificial Intelligence, Modelling and Simulation*, IEEE, Nov. 2014, pp. 39–43, doi: 10.1109/aims.2014.12.
[28] H. Devos *et al.*, "Reliability of P3 Event-Related Potential During Working Memory Across the Spectrum of Cognitive Aging," *Frontiers in Aging Neuroscience*, vol. 12, Oct. 2020, doi: 10.3389/fnagi.2020.566391.
[29] Y. Zhang, C. Wang, F. Wu, K. Huang, L. Yang, and L. Ji, "Prediction of working memory ability based on EEG by functional data analysis," *Journal of Neuroscience Methods*, vol. 333, p. 108552, Mar. 2020, doi: 10.1016/j.jneumeth.2019.108552.
[30] Z. Mahmoodin, W. Mansor, K. Y. Lee, and A. Z. A. Zainuddin, "Electroencephalogram Theta-Beta Band Power Features Generated from Writing for the Classification of Dyslexic Chidren," in *2018 IEEE-EMBS Conference on Biomedical Engineering and Sciences (IECBES)*, IEEE, Dec. 2018, pp. 288–292, doi: 10.1109/iecbes.2018.8626608.

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