# A Review on Examination Methods of Types of Working Memory and Cerebral Cortex in EEG Signals

Mehran Emadi<sup>1</sup>, Mohsen Karimi<sup>2</sup>, Fatemeh Davoudi<sup>3</sup>

1- Department of Electrical Engineering, Mobarakeh Branch, Islamic Azad University, Mobarakeh, Isfahan, Iran. Email: emadi.mehran49@gmail.com (Corresponding author)

2- Department of Bioelectric and Biomedical Engineering, School of Advanced Technologies in Medicine, Isfahan, Iran. Email: Mohsen.karimi25@gmail.com

3- Iran university science and technology (IUST) School of Electrical Engineering, Tehran, Iran.

 $Email: f\_davoudi@cmps2.iust.ac.ir$ 

Received: 10 July 2023

Revised: 26 July 2023

Accepted: 23 August 2023

### **ABSTRACT:**

Brain is the most important organ in human body. All of our memories are saved on brain. Brain activity is analyzed by electroencephalogram signals (EEG). Brain activity and memory signal represent brain activity that can be recorded in different brain regions. Electroencephalography signal analysis can provide complete and comprehensive information about brain activity. Working of brain memory as an activity is analyzed by EEG. The main purpose of this research is to review the types of memory and especially working memory in humans by processing of EEG. In this regard, memory and types of memory have been discussed at the beginning. Then the brain activity and memory signal, recording method, electrode placement, brain potentials are discussed. Then, the complexity of the brain activity and memory signal in memory has been investigated. Then, memory and its relationship with brain activity and memory signal have been discussed. Areas affected by memory are expressed in the brain. After the researches about brain activity and memory signals in memory.

KEYWORDS: Working memory, Cerebral cortex, Electroencephalography, Brain

# 1. INTRODUCTION

Memory is a complex system that includes different functions several and cognitive processes. Physiologically, the formation of memory in the human brain is caused by changes in the ability of synaptic conduction from one neuron to another[1, 2]. These changes, in turn, lead to the emergence of new pathways or facilitated pathways to guide messages in the neural circuits of the brain, and these new or facilitated pathways are called memory pathways [<sup>Y</sup>]. The importance of these pathways is that once the memory pathways are formed, they can be activated by mental thought to recreate memories. Experiments carried out in lower animals have shown that memory paths are created at all levels of the nervous system[3-6]. Even spinal reflexes can undergo slight changes in response to repeated stimulation of the spinal cord, and this is part of the memory process [<sup>V</sup>]. Memory is divided into short-term memory (STM) and

long-term memory (LSTM) based on the amount of time that information is stored[7-11]. From another point of view, memory is considered and that is working memory [<sup>\vert</sup>].Working memory is a short-term storage system that involves the use of information as long as it is available in the environment. Working memory is essential for people's cognitive functions and means a limited capacity to store information for a few seconds in the field of cognitive function. Previous studies have shown that working memory capacity is of great importance in a wide range of high-order cognitive functions such as reasoning. problem solving, and language comprehension[8, 12-14]. When there is a disturbance in working memory, cognitive skills are also affected and the overall performance of executive activities is disturbed. If functional disabilities cause problems and disturbances in people's daily activities, it is said that the person has a memory disorder [1V].

Paper type: Research paper

DOI: 10.30486/mjtd.2023.1991049.1041

How to cite this paper: M. Emadi, M. Karimi and F. Davoudi, "A Review on Examination Methods of Types of Working Memory and Cerebral Cortex in EEG Signals", *Majlesi Journal of Telecommunication Devices*, Vol. 12, No.3, pp.161-169, 2023.

The purpose of this paper is to review Brain activity and memory signal processing methods in order to investigate the relationship between working memory function and brain EEG signal. Therefore, in the following, the Brain activity and memory signal is first introduced, and then the processing of the Brainactivity and signal and its relationship with memory working memory are examined. At the end, the research conducted in this topic will be analyzed. The conclusion of the article is presented in the last part.

# 2. ELECTROENCEPHALOGRAM

The human brain is the main controller of all reactions, feelings, thoughts, internal and external behaviors, which consists of many parts. Decision-making, planning and judgment are done by the frontal part in the front of the brain, and in the back of the brain, the visual perception area, and speech is also done in the temporal part of the brain. The cerebellum is also responsible for balance and coordination. Communication between different parts of the brain is done through nerve cells. Each nerve cell consists of three parts: cell body, axon, and dendrite, and cells communicate with each other through axon and dendrite. Nerve waves, which are the basis of any kind of function, are transmitted to the next cells through these axons and neurons. The transmission of these waves inside the cells is electrical and between two cells, chemical, which is done in a very narrow space between two cells, and when the nerve wave enters the end of a cell, a specific neurotransmitter is injected into the synaptic space. This neurotransmitter attaches to its special receptors in the next cell in the form of a lock and key, thereby causing the cell to undergo a change in electrical charge and finally leading to the transmission of the nerve wave along the next cell [23].So far, many

methods have been used to examine brain function, such as positron emission tomography, medicine nuclear imaging. functional magnetic resonance imaging, and other methods, in addition to requiring high costs, sometimes Unpleasant pleasure from. They are also looking for injecting radioactive materials and placing them in a strong magnetic field[Y٤-YY]. In the meantime. electroencephalography, which records the electrical activity of the brain, is cost-effective and has no side effects.Electroencephalography or EEG is a non-invasive recording of the brain's electrical activity through the installation of surface electrodes on the head[15-17]. In general, in an EEG system, the electrical effect of the activity of brain neurons is transmitted to the device through electrodes installed on the head, and after amplification and noiseremoval, it is recorded and displayed as a time signal. The recorded signal can be analyzed directly or after computer processing by a doctor or neuroscientist. With the help of electroencephalography, it is possible to determine the amount of that activity and the failure of the involved brain areas in all kinds of brain activities [<sup>ү</sup>·]. As a result, the examination and analysis of the recorded signal electroencephalography through plays an effective role in a wide range of diagnostic and research applications, such as the following:

- 1-Diagnosis and recognition of cerebral brain damage and determining its location.
- 2- Examining epileptic attacks.
- 3-Diagnosis and recognition of mental disorders
- 4-Studying sleep and investigating its disorders
- 5-Observing and analyzing brain responses to sensory stimuli.
- 6-Research related to Brain Computer Interface (BCI) [<sup>Y</sup>].

The desired subband	Characteristics	Operating frequency	
Delta subband	Seen in babies, deep sleep and in some brain diseases	Between 0.5 and 3.5 Hz	
Theta subband	Seen in regional and temporal areas of the brain, and children, seen in adults who are depressed and under psychological pressure.	ren, seen in adults who are Between 4 and 7 Hz	
Alpha subband	Seen in normal people and in a state of consciousness with closed eyes, recorded in calm conditions, presence in the back of the head	eyes, recorded in Botwoon 8 and 13 Hz	
SMR wave	Being seen in a relaxed state and reducing	n in a relaxed state and reducing Between 12 and 15 Hz	

Table 1. Characteristics of frequency sub bands in the EEG signal.

### Vol. 12, No. 3, September 2023

	anxiety		
D. (		Beta 1 sub band: between 14 and 30 Hz	
Beta subband	Seen in intense brain activities in the frontal and parietal regions, seen during thinking	Beta (gamma) 2 sub band: between 30 and 50 Hz	
		Intermediate beta sub band: between 16 and 20 Hz	
Gamma subband	Being seen in cognitive activities such as intense and focused attention, stimulation of emotions	Between 30 and 50 Hz	
The desired sub band	Characteristics	Operating frequency	
Delta subband	Seen in babies, deep sleep and in some brain diseases	Between 0.5 and 3.5 Hz	
Theta subband	Seen in regional and temporal areas of the brain, and children, seen in adults who are depressed and under psychological pressure.	Between 4 and 7 Hz	
Alpha subband	Seen in normal people and in a state of consciousness with closed eyes, recorded in calm conditions, presence in the back of the head	Between 8 and 13 Hz	
SMR wave	Being seen in a relaxed state and reducing anxiety	Between 12 and 15 Hz	
		Beta 1 subband: between 14 and 30 Hz	
Beta subband	Seen in intense brain activities in the frontal and parietal regions, seen during thinking	Beta (gamma) 2 subband: between 30 and 50 Hz	
		Intermediate beta subband: between 16 and 20 Hz	
Gamma subband	Being seen in cognitive activities such as intense and focused attention, stimulation of emotions	Between 30 and 50 Hz	

Brain activity and memory signal recordings from patients are usually done while awake. However, depending on the type of test, the person may be asked to keep their eyes open or closed. With the eyes open, sometimes through a flashing light (photic), the patient's sensitivity to light stimulation is measured. An EEG is a dynamic ensemble that changes with any physical or non-physical change. The sensitivity of these signals is so high that they change even by blinking. In order to analyze these signals more precisely, they are divided into different sub-bands based on different frequencies. The EEG signal is usually in the frequency range of 0.5 Hz to 50 Hz [<sup>Yo</sup>]. In the presented division, the created and known sub bands are: delta sub bands, their small beta sub bands, SMR sub band, beta sub band and finally gamma sub band, Table (1) shows the characteristics of these sub bands<sup>[77]</sup>.

# 3. BRAIN ACTIVITY AND MEMORY SIGNAL PROCESSING

The use of non-linear methods in the activity and memory processing of Brain signals has a relatively long history. Many activities deal with the calculation of the signal correlation dimension. However, the correlation dimension is only for stationary time series defined by a low-dimensional dynamical system moving around an Attractor[18-20]. Therefore, this criterion does not have a suitable ability in evaluating EEG performance, because EEG is non-static by definition and time-dependent changes of EEG power are modeled in different frequency bands with stimulus noises that have variable variance over time  $[^{\forall} \cdot ]$ . Klinesh states that high-scale synchrony in the alpha band blocks information processing because many neurons' oscillations occur with the same phase and frequency. On the other hand, non-synchrony in the alpha band reflects real cognitive processing because different neural networks start to operate with frequencies different and phases [ [ ]. Increasing a synchronicity while using memory

leads to increasing complexity. Also, Li and et al. in  $[\[mathbf{mathcharger}]$  showed that the fractal dimension value (as a feature expressing the complexity) of the EEG signal is inversely related to the activity of the neuronal population and can be used as a useful measure to reveal changes in the synchrony of tons under Specific mental conditions are used. The term complexity for nonlinear EEG analysis has been widely used for studies of cortical dynamics in different conditions. The degree of EEG complexity determines important information about the structural components of the data such as oscillatory components (such as diagnosing or predicting an epileptic attack from EEG, diagnosing Alzheimer's disease, visual cortex function, working memory dynamics, etc.). In order to clarify the complexity, two concepts are examined  $[\gamma\gamma]$ . The first concept is that the functional source is the part or parts of the brain that participate in the registration process from a sensor. Functional source is an operational concept that must not correspond to an anatomical part of the brain and is neutral to the local source and volume transfer, and briefly corresponds to a part of the brain that is measured in a specific location. The second concept is a functional network, which is defined as a complete matrix of all pairs of between functional correlations sources. Therefore, dynamic complexity is defined as random connections or lack of connections between dynamic elements of the system. This definition can be easily interpreted as the term functional network or functional resource introduced above [٣٤]. The dynamic complexity of a functional network is related to the lack of correlation between its functional resources. In other words, the higher level of synchronization between functional resources in a functional network corresponds to the low dynamic complexity [<sup>ro</sup>]. The EEG signal results from the sum of a large number of postsynaptic activities spread in space, which is functionally connected and interactive between cortical neurons and neural groups such as functional sources. Therefore, the time series has a complex structure that reflects the underlying complexity of neural generators. The greater the number of independent processes participating in the EEG, the greater the complexity of the time series. EEG complexity may reflect the number of states in which a system results from the interaction between elements. On the other hand, the dynamic complexity of a system can be

interpreted by measuring the degree of freedom of the system.

# 4. MEMORY CONNECTION WITH BRAIN ACTIVITY AND MEMORY SIGNAL

Working memory means the ability to retain and maintain information in a short period of time, which is divided into the sub-sections of primary information encoding, retention and retrieval. Since working memory has a great impact on cognitive processes, many studies have identified neural substrates in various working memory processes  $[\gamma \gamma]$ . As stated, Brain activity and memory signal power can determine the degree of signal synchronicity and is actually a measure that can model the capacity or function of cortical information processing. Based on this, so far, many conducted researchers have been on the relationship between memory function and brain EEG signal power in different sub-bands, and the relationship between memory and different Brain activity and memory signal rhythms during the process of memorization and recall has been evaluated in many researches, theta rhythm is related It is known with memory  $[\forall \forall]$ .



**Fig. 1**. Different stages of working memory including encoding, retention and retrieval of information [2].

For example, in the research conducted by Sarnthein and et al.  $[^{\Upsilon A}]$ , an increase in theta band coherence between the prefrontal and back regions was observed during working memory activity.

Also, in  $[{}^{rq}]$ , an increase in theta power when responding to words and facial images in the memory process has been reported. In addition, an increase in theta power has been reported when working

memory load increases. In  $[\mathfrak{t}, \mathfrak{d}]$ , an increase in the power of the theta band in the frontal area and in the middle area was reported during the increase of the working memory load. In several studies, gamma rhythms  $[\xi_1]$  and SMR  $[\gamma_1]$  associated with memory have been introduced. For example, Howard and et al showed that during the process of temporary memorization of letters in working memory, the gamma band activity increases, and when the working memory load increases, the gamma band activity also increases, and vice versa after the subjects answer[<sup>£</sup><sup>γ</sup>]. Gamma band activity also decreases due to stimuli and reducing working memory load  $[\mathfrak{t}^{\mathfrak{r}}]$ . Haarnan and et al  $[\mathfrak{t}^{\mathfrak{t}}]$  also reported an increase in SMR band congruence between frontal and back regions during word repetition in semantic working memory [<sup>£</sup><sup>£</sup>]. Honkanen and et al also showed that gamma band oscillations are effective in maintaining working memory information  $[\mathfrak{s}\circ]$ . Alpha rhythm related to memory has been reported in several studies [ $^{\psi}$ ,  $^{\psi \gamma}$ ]. Gevins and et al. investigated the activity of two subbands, alpha and theta, during memory activity

#### Vol. 12, No. 3, September 2023

[49]. The results showed that with increasing memory workload, theta band activity increases in the frontal areas, while alpha activity decreases in the occipital and parietal areas, and the higher the memory activity, the greater the increase in the theta band and decrease in the alpha band (figure 2). Berger and et al showed that information processing in long-term semantic memory and information retrieval is associated with a decrease in high alpha band power, and better performance is associated with a greater decrease. They also showed that increasing the power of the high alpha band keeps the memory paths free from interference and unrelated activities [<sup> $\varphi$ </sup>V]. Meltzer and et alexamined the changes in gamma, theta and alpha band power during increasing working memory load. They observed that the power of the gamma band increases in all areas of the head, especially in the back of the head, due to the increase in the load of the working memory, but the power of the gamma band and the alpha band increases in some areas and decreases in some areas  $[^{\varphi}\Lambda]$ .



**Fig. 2**: Average distribution of power spectrum mapping in frequency peak of alpha and theta bands in working memory activity. With the increase of working memory activity load, theta power increases and the theta band in areas with medium and high working memory load has a higher level compared to low working memory load. But the power of the alpha band decreases uniformly with the increase of working memory load [\$?]

It has also been shown in [2] that all three bands, gamma, theta and alpha, have an effect on working memory activity, but each one has its own task. They showed that gamma band oscillations are generally involved in maintaining information in working memory, while alpha band oscillations are responsible for preventing the interference of information from other activities with working memory information. Theta band oscillations also sequence information in working memory. Klimesch states that two factors can cause changes in the power of EEG signal bands  $[7^{1}]$ .

- Tonic changes such as age that cause changes in EEG.
- Phasic or event-dependent changes that occur as a result of performing an activity. Table 2 shows the changes in alpha and theta band power during two types of changes

Table 2 shows the changes in alpha and theta band power during two types of changes.

**Table 2**.Separation of tonic and phasic changes in alpha and theta band power according to cognitive function [٣)].

	Decreased performance		Increase performance	
	theta power	alpha power	theta power	alpha power
Tonic variation	Decrease	Increase	Increase	Decrease
Physic changes	Increase	Decrease	Decrease	Increase

Klimesch has shown that the alpha rhythm is specifically related to semantic memory in that alpha activity is reduced after presentation of a semantic stimulus. Also, Klimesch has stated that during real activity demands, the of suppression amount alpha power is positively related cognitive to function (especially in memory function), while the opposite is true for the theta band, and the amount of theta band synchrony is related to good performance. has it. From Figure 3, it is clear that during the memory activity, the alpha power is suppressed, but the theta band power is increased. Therefore, if we compare the EEG power in the test state with the resting state, the

power of the alpha band should decrease (nonsynchrony occurs) and the power of the theta band should increase (synchrony occurs). Also, in an experiment of two groups of people with memory good and bad were compared with each other. The results showed that people with good memory significantly have higher alpha band power and lower theta power[ $[r_1]$ ].



Fig. 3. EEG signal power changes during rest.

(dotted line) and during memory activity (solid line)  $[r_1]$ 

As can be seen, contrary to the many researchers conducted regarding memory and its relationship with Brain activity and memory signal, there is still disagreement regarding the choice of rhythm related to memory, which is due to the complexity of the memory structure and the influence of various cognitive factors such as mood, The level of intelligence and the level of attention of a person is on memory. Also, it is better to consider the EEG signal as a non-linear time series ["]and use non-linear for processing. Therefore. techniques its research has been done on the relationship function and brain between memorv EEG signal using non-linear techniques. For in [<sup>ma</sup>]used example, Talebi and et al. quantitative approximate entropy and regression analysis investigate memory to function and brain EEG signal during the injection of midazolam (a drug that causes amnesia) as a non-linear measure. The results showed that drug injection increases the complexity of the EEG signal. Abasolo and et al. in [<sup>eq</sup>]also used approximate entropy as a non-linear measure to quantify the time series signal routine to distinguish healthy people from people with Alzheimer's disease. They observed that the approximate entropy value is lower in Alzheimer's patients, which means less complexity reduction. This reduction in

complexity is caused by the reduction of neurotransmitters and local neural network approximate connections. They showed that entropy is a suitable tool to reveal hidden characteristics of vital signals that are not revealed by linear (spectral) analysis. In  $[\Delta \cdot]$ , wavelet entropy has been used as an EEG signal complexity evaluation tool to investigate changes in working memory load at seven different levels during the cognitive process. The results showed that the complexity of the signal increases with the increase of working memory load. Therefore, it can be seen that so far, the EEG signal has been evaluated with different criteria during the use of working memory. The common point of all the works done is that the complexity of the Brain activity and memory signal increases during the use of memory, and the higher the complexity of the signal during the use of memory, the better the performance.

# **5. CONCLUSION**

In this research, the relationship between memory function and brain EEG signal was discussed. So far a lot of research has been on the relationship between memory done and brain EEG signal power in function different sub-bands.Relationship between and different brain activity memorv and memory signal rhythms during the process of remembering. Despite the many researches done on memory and its relationship with Brain activity and memory signal, there is still a difference of opinion regarding the choice of rhythm related to memory. The reasons for which are the complexity of the memory structure. Another reason is the influence of various cognitive factors such as mood intelligence and attention on brain. Research has also been done on the relationship between memory function and brain EEG signal using different non-linear criteria, which is the common point of all the work done is that the complexity of the brain activity and memory signal increases while using memory. The greater the complexity of the signal while using memory, the better the person's performance.

# REFERENCES

- [1] F. Mahmudi, M. Soleimani, and M. Naderi, "Some Properties of the Maximal Graph of a Commutative Ring," *Southeast Asian Bulletin* of Mathematics, vol. 43, no. 4, 2019.
- [2] B. Heidari, and M. Ramezanpour, "Reduction of intra-coding time for HEVC based on temporary

direction map," Journal of Real-Time Image Processing, vol. 17, pp. 567-579, 2020..

- [3] A. R. Khan *et al.*, "Authentication through gender classification from iris images using support vector machine," *Microscopy research and technique*, vol. 84, no. 11, pp. 2666-2676, 2021.
- [4] S. Aryanmehr, M. Karimi, and F. Z. Boroujeni, "CVBL IRIS gender classification database image processing and biometric research, computer vision and biometric laboratory (CVBL)," in 2018 IEEE 3rd International Conference on Image, Vision and Computing (ICIVC), 2018, pp. 433-438: IEEE.
- [5] A. Raftarai, R. R. Mahounaki, M. Harouni, M. Karimi, and S. K. Olghoran, "Predictivemodels of hospital readmission rate using the improved AdaBoost in COVID-19," in *Intelligent Computing Applications for COVID-19*: CRC Press, 2021, pp. 67-86.
- [6] M. Emadi, Z. Jafarian Dehkordi, and M. Iranpour Mobarakeh, "Improving the Accuracy of Brain Tumor Identification in Magnetic Resonanceaging using Super-pixel and Fast Primal Dual Algorithm," International Journal of Engineering, vol. 36, no. 3, pp. 505-512, 2023.
- [7] R. Nardone *et al.*, "Visuomotor integration in early Alzheimer's disease: A TMS study," *Journal of the neurological sciences*, p. 120129, 2022.
- [8] A. J. Moshayedi *et al.*, "E-Nose design and structures from statistical analysis to application in robotic: a compressive review," *EAI Endorsed Transactions on AI and Robotics*, vol. 2, no. 1, pp. e1-e1, 2023.
- [9] A. Rehman, M. Harouni, M. Karimi, T. Saba, S. A. Bahaj, and M. J. Awan, "Microscopic retinal blood vessels detection and segmentation using support vector machine and K- nearest neighbors," *Microscopy research and technique*, vol. 85, no. 5, pp. 1899-1914, 2022.
- [10] M. Karimi, M. Harouni, A. Nasr, and N. Tavakoli, "Automatic lung infection segmentation of covid-19 in CT scan images," in *Intelligent Computing Applications for COVID-19*: CRC Press, 2021, pp. 235-253.
- [11] S. A. Mousavizadeh Mobarakeh and M. Emadi, "Improvement of the Identification Rate using Finger Veins based on the Enhanced Maximum Curvature Method using Morphological Operators," Majlesi Journal of Telecommunication Devices, vol. 11, no. 1, 2022.
- [12] M. Emadi and M. Emadi, "Human face detection in color images using fusion of Ada Boost and LBP feature," *Majlesi Journal of*

*Telecommunication Devices*, vol. 9, no. 1, pp. 23-33, 2020.

- [13] J. Heo and G. Yoon, "EEG studies on physical discomforts induced by virtual reality gaming," *Journal of Electrical Engineering & Technology*, vol. 15, no. 3, pp. 1323-1329, 2020.
- [14] M. Soleimani, F. Mahmudi, and M. H. Naderi, "On the Maximal Graph of a Commutative Ring," *Mathematics Interdisciplinary Research*, 2021.
- [15] M. Soleimani, M. H. Naderi, and A. R. Ashrafi, "TENSOR PRODUCT OF THE POWER GRAPHS OF SOME FINITE RINGS," Facta Universitatis, Series: Mathematics and Informatics, pp. 101-122, 2019.
- [16] M. Karimi, M. Harouni, and S. Rafieipour, "Automated medical image analysis in digital mammography," in *Artificial intelligence and internet of things*: CRC Press, 2021, pp. 85-116.
- [17] H. Koshino, T. Minamoto, K. Yaoi, M. Osaka, and N. Osaka, "Coactivation of the default mode network regions and working memory network regions during task preparation," *Scientific reports*, vol. 4, no. 1, pp. 1-8, 2014.
- [18] M. Karimi, M. Harouni, E. I. Jazi, A. Nasr, and N. Azizi, "Improving monitoring and controlling parameters for alzheimer's patients based on iomt," in *Prognostic models* in healthcare: Ai and statistical approaches: Springer, 2022, pp. 213-237.
- [19] M. Harouni, M. Karimi, and S. Rafieipour, "Precise segmentation techniques in various medical images," Artificial Intelligence and Internet of Things: Applications in Smart Healthcare, vol. 117, 2021.
- [20] S. Borhani et al., "Gauging Working Memory Capacity From Differential Resting Brain Oscillations in Older Individuals With A Wearable Device," Frontiers in Aging Neuroscience, vol. 13, p. 36, 2021.
- [21] G. H. Cattan, A. Andreev, C. Mendoza, and M. Congedo, "A comparison of mobile VR display running on an ordinary smartphone with standard PC display for P300-BCI stimulus presentation," *IEEE Transactions on Games*, 2019.
- [22] A. Badura, A. Masłowska, A. Myśliwiec, and E. Piętka, "Multimodal Signal Analysis for Pain Recognition in Physiotherapy Using Wavelet Scattering Transform," *Sensors*, vol. 21, no. 4, p. 1311, 2021.
- [23] B. Wan, Q. Wang, K. Su, C. Dong, W. Song, and M. Pang, "Measuring the Impacts of Virtual Reality Games on Cognitive Ability Using EEG Signals and Game Performance Data," *IEEE Access*, vol. 9, pp. 18326-18344, 2021.

- [24] R. Daniel and S. Pollmann, "Striatal activations signal prediction errors on confidence in the absence of external feedback," *Neuroimage*, vol. 59, no. 4, pp. 3457-3467, 2012.
- [25] H. Dabas, C. Sethi, C. Dua, M. Dalawat, and D. Sethia, "Emotion classification using EEG signals," in Proceedings of the 2018 2nd International Conference on Computer Science and Artificial Intelligence, 2018, pp. 380-384.
- [26] G. Cattan, A. Andreev, C. Mendoza, and M. Congedo, "The impact of passive headmounted virtual reality devices on the quality of EEG signals," in Workshop on Virtual Reality Interaction and Physical Simulation, 2018: The Eurographics Association.
- [27] M. Harouni, M. Karimi, A. Nasr, H. Mahmoudi, and Z. Arab Najafabadi, "Health monitoring methods in heart diseases based on data mining approach: A directional review," in Prognostic models in healthcare: Ai and statistical approaches: Springer, 2022, pp. 115-159.
- [28] F. Mahmudi and M. Soleimani, "Some results on Maximal Graph of a Commutative Ring," 2016.
- [29] [29] A. Jafarzadeh and M. Soleimani, "NON-VANISHING ELEMENTS AND ZEROS OF CHARACTERS OF FINITE GROUPS: A REVIEW," in 42nd Annual Iranian Mathematics Conference, 2011.
- [30] P. A. Dudchenko, "An overview of the tasks used to test working memory in rodents," *Neuroscience & Biobehavioral Reviews*, vol. 28, no. 7, pp. 699-709, 2004.
- [31] W. Klimesch, "EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis," *Brain research reviews*, vol. 29, no. 2-3, pp. 169-195, 1999.
- [32] X. Li, Z. Deng, and J. Zhang, "Function of EEG temporal complexity analysis in neural activities measurement," in *International Symposium on Neural Networks*, 2009, pp. 209-218: Springer.
- [33] N. Najafabadi, and M. Ramezanpour, "Mass center direction-based decision method for intraprediction in HEVC standard," *Journal* of *Real-Time Image Processing*, vol. 17, no. 5, pp. 1153-1168, 2020..
- [34] W. Kolata and S. Kolata, "A model of working memory capacity in the radial-arm maze task," *Journal of Mathematical Psychology*, vol. 53, no. 4, pp. 242-252, 2009.
- [35] N. Talebi, A. M. Nasrabadi, and T. Curran, "Investigation of changes in EEG complexity during memory retrieval: the effect of

midazolam," *Cognitive neurodynamics*, vol. 6, no. 6, pp. 537-546, 2012.

- [36] X. Wang, M. Tugcu, J. E. Hunter, and D. M. Wilkes, "Exploration of configural representation in landmark learning using working memory toolkit," *Pattern recognition letters*, vol. 30, no. 1, pp. 66-79, 2009.
- [37] S. Nikolin, Y. Y. Tan, A. Schwaab, A. Moffa, C. K. Loo, and D. Martin, "An investigation of working memory deficits in depression using the n-back task: A systematic review and meta-analysis," *Journal of Affective Disorders*, 2021.
- [38] J. Sarnthein, H. Petsche, P. Rappelsberger, G. Shaw, and A. Von Stein, "Synchronization between prefrontal and posterior association cortex during human working memory," *Proceedings of the National Academy of Sciences*, vol. 95, no. 12, pp. 7092-7096, 1998.
- [39] M. Lui, K. F. Lui, A. C.-N. Wong, and J. P. Rosenfeld, "Suppression of 12-Hz SSVEPs when familiar viewing faces: An electrophysiological index to detect recognition." International Journal of Psychophysiology, vol. 133, pp. 159-168, 2018.
- [40] U. Maurer, S. Brem, M. Liechti, S. Maurizio, L. Michels, and D. Brandeis, "Frontal midline theta reflects individual task performance in a working memory task," *Brain topography*, vol. 28, no. 1, pp. 127-134, 2015.
- [41] C. Tremmel, "Estimating Cognitive Workload in an Interactive Virtual Reality Environment Using Electrophysiological and Kinematic Activity," Old Dominion University, 2019.
- [42] M. W. Howard *et al.*, "Gamma oscillations correlate with working memory load in humans," *Cerebral cortex*, vol. 13, no. 12, pp. 1369-1374, 2003.
- [43] J. B. Sala and S. M. Courtney, "Binding of what and where during working memory

maintenance," *Cortex*, vol. 43, no. 1, pp. 5-21, 2007.

- [44] H. J. Haarmann and K. A. Cameron, "Active maintenance of sentence meaning in working memory: Evidence from EEG coherences," *International journal of psychophysiology*, vol. 57, no. 2, pp. 115-128, 2005.
- [45] R. Honkanen, S. Rouhinen, S. H. Wang, J. M. Palva, and S. Palva, "Gamma oscillations underlie the maintenance of feature-specific information and the contents of visual working memory," *Cerebral cortex*, vol. 25, no. 10, pp. 3788-3801, 2015.
- [46] F. Concatto, E. J. Legal, and A. R. G. Ramirez, "On-line Measurement of Working Memory in Individuals with Aphasia using Electroencephalographic Signals," in 2021 16th Iberian Conference on Information Systems and Technologies (CISTI), 2021, pp. 1-4: IEEE.
- [47] B. Berger, S. Omer, T. Minarik, A. Sterr, and P. Sauseng, "Interacting memory systems—does EEG alpha activity respond to semantic long-term memory access in a working memory task?," *Biology*, vol. 4, no. 1, pp. 1-16, 2015.
- [48] J. A. Meltzer *et al.*, "Effects of working memory load on oscillatory power in human intracranial EEG," *Cerebral Cortex*, vol. 18, no. 8, pp. 1843-1855, 2008.
- [49] D. Abásolo, R. Hornero, P. Espino, J. Poza, C. I. Sánchez, and R. de la Rosa, "Analysis of regularity in the EEG background activity of Alzheimer's disease patients with Approximate Entropy," Clinical neurophysiology, vol. 116, no. 8, pp. 1826-1834, 2005.
- [50] P. Zarjam, J. Epps, F. Chen, and N. H. Lovell, "Classification of working memory load using wavelet complexity features of EEG signals," in International Conference on Neural Information Processing, 2012, pp. 692-699: Springer.