Computer Gaming and Physiological Changes in the Brain: An Insight from QEEG Complexity Analysis

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Abstract

To compare the pattern of brain waves in video game addicts and normal individuals, a case–control study was carried out on both. Thirty participants were recruited from 14 to 20 years old males from two gaming centers. Twenty healthy participants were gathered from different schools in Tehran using the available sampling method. The QEEG data collection was performed in three states: closed-eye and open-eye states, and during a working memory task. As expected, the power ratios did not show a significant difference between the two groups. Regarding our interest in the complexity of signals, we used the Higuchi algorithm as the feature extractor to provide the input materials for the multilayer perceptron classifier. The results showed that the model had at least a 95% precision rate in classifying the addicts and healthy controls in all three types of tasks. Moreover, significant differences in the Higuchi Fractal Dimension of a few EEG channels have been observed. This study confirms the importance of brain wave complexity in QEEG data analysis and assesses the correlation between EEG-complexity and gaming disorder. Moreover, feature extraction by Higuchi algorithm can render support vector machine classification of the brain waves of addicts and healthy controls more accurate.

Keywords Video gaming addiction · Features selection · Machine learning · Higuchi fractal dimension · Adolescent · Brain wave complexity

Introduction

During the last three decades, video games have become one of the major pastimes and one of the most growing industries worldwide (Sepehr & Head, 2012). 67% of all Americans play video games, for example. This is a highly varied phenomenon, ranging from primary games to highly advanced 3D ones, and is an increasingly frequent activity worldwide. Today, computer games include sophisticated virtual worlds, online competitions, and multiplayer strategic games. In 2008, the American National Purchase Diary (NPD) group reported that 3% of the 174 million players using PC, MAC, or game consoles were extreme gamers who are playing an average of 45 h a week. NPD reported that the percentage of extreme gamers had increased to 4% by 2010 (https://www.npd.com/).

The internet gaming disorder (IGD) is a growing and prolonged behavioral pattern of gaming leading to behavioral and cognitive syndromes. It is the increasing loss of control over gaming, tolerance, and the presence of withdrawal syndrome. The addicts are usually 12 to 20 years old and spend 8–10 h a day or more playing video games. Preventing them from playing can lead to tension and anger and they may spend long stretches of time playing without food and sleep (American Psychiatric Association, 2013). According to the reports given by scientists and psychologists, gamers are increasing their playing time to a problematic degree. Investigations have also shown that, in some cases, gaming may seriously damage subjects' school, work, and social relationships in the real world.

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Even though video gaming has some positive effects (including good concentration, memory, and solving skills), researchers have shown that excessive use of computer games may lead to negative effects like stress, aggressive behavior, verbal memory deficiency, depression, lowered cognitive abilities, sleeping disorders, anxiety and, behavioral addiction. Moreover, clinical evidence has shown that subjects addicted to online games experience biopsychological symptoms and complications. These symptoms may include the traditional symptoms of drug addiction such as hangover, changes in mood, adaptability, withdrawal, conflict, and recurrence symptoms. On the other hand, Given the increasing advancement of technology and, subsequently, computer games, the prevalence of this abnormality in societies can be expected. Thus, there is a growing need for further investigation of this phenomenon and its potential effects on people.

The first study about video gaming addiction was done by Ross, Finestone, and Lavin, who referred to it as "space invader obsession"(Ross et al., 1982), 10 years after the first video game release. Soper and Miller are pioneers in calling this disorder a kind of addictive behavior (Soper & Miller, 1983). The first assessment and questionnaire was conducted by Kimberly Young (Young, 1998). In 2013 after numerous studies with a variety of methods, DSM5 defined internet gaming disorder as addictive behavior. According to the Diagnostic and Statistical Manual of Psychiatric Disorders (DSM-5), computer-based or online gaming addiction is a preoccupation with playing games. It usually includes a group of players, often resulting in several consequences within 5 to 12 weeks (American Psychiatric Association, 2013).

Working memory plays an important role in facing addiction; thus it is unfavorably affected by addiction. Therefore, studying the consequences of gaming addiction on working memory is one of the interesting research subjects; however, it needs careful task designing. In task designing, it is important to just peruse a function by controlling other functions as much as possible (Hollnagel, 2003). Thus, a mental calculation task is considered a cognitive task. Related to working memory, a mental calculation is a routine, everyday ability that everyone possesses, regardless of their level of education. Moreover, focusing on the working memory, we tried to limit brain activity in other areas like auditory and visionary activities. Consequently, we assessed and compared the working memory of two groups via a mental calculation task.

Neurobiological differences have been discovered between healthy controls and individuals with Internet Gaming Disorder using PET, VBM, fMRI, rsfMRI, and EEG studies. As a popular technique in the assessment of the neurobiological differences, EEG is used to compare (i) excessive and addictive gaming, (ii) gaming addiction and other comorbid disorders, and (iii) gaming addiction (miscellaneous).

Brain dynamics are highly complicated, having multiple spatial–temporal scales. Thus, non-linear dynamics methods have been used to analyze the brain's neurophysiological outputs. Stochasticity, determinism, causation, and correlations of neurodynamics are epitomized and quantified on the complexity measures of brain waves and other biosignals data of the brain. Causality, correlation, and stochastic phenomena turn QEEG data into a complex time series. There are several lines of evidence suggesting that this aspect of the brain waves is influenced by cognitive disorders. Thus, various complexity measures have been put forward to analyze EEG data, including measures developed using random fractal theory, information theory, and chaos theory.

Gao et al. Have described the different approaches to analyzing the complex dynamics. They distinguish between chaos and random phenomena. Chaos theory considers irregular behaviors in a complex system. These behaviors are deterministic and are caused by only a few degrees of freedom. Here, noise or intrinsic randomness is not of primary concern. In contrast, randomness is the pivotal principle of random fractal theory and information theory. They consider the dynamics of the system to be inherently random (Gao et al., 2007). While long-range correlations form the subject of random fractal theory, short-range correlations are considered in information theory. in their study on the relations among different complexity measures for EEG, Gao et al. "found that the variations of these complexity measures with time are either similar or reciprocal." (Gao et al., 2011). In what follows, the salient steps of our study will be presented.

The Higuchi Algorithm Feature Extraction and Partition Membership Feature Selection Method

Feature extraction is the process of transforming original data to remove redundant or irrelevant information and producing a much smaller and more manageable data set of more discriminator variables. The goal of feature selection, however, is to reduce overfitting, improve accuracy, and decrease training time. After feature extraction and feature selection, the resulting features are valuable if they are highly correlated with the class and uncorrelated with each other. Hence, we are interested in the feature subset containing the minimum number of features that contribute to accuracy the most.

Fractal theory can be used to extract features from a series. The Higuchi Fractal Dimension (HFD) algorithm is a method for measuring the fractal dimension of discrete-time sequences (Higuchi, 1988; Kesić & Spasić, 2016). It is a criterion of the complexity and self-similarity of the signal.

For time series *x[1], x[2],..., x[n]*, the Higuchi fractal can be calculated as:

The original series is converted to *k* new series via Higuchi's algorithm; thus, from *[x₁, x₂, …, x_N]*, where *N* is the length of the original time series, the following series are obtained:

$$X_m, X_{m+k}, X_{m+2k}, \cdots, X_{m+[(N-m)/k]k}$$

where m is initial time; k is the time interval in the way that $m = 1, 2, …, k$. $L(m, k)$ is the length of each time series:

$$L(m,k) = \frac{\sum_{i=2}^{[(N-m)/k]} \left| x_{m+ik} - x_{m+(i-1)k} \right| (N-1)}{\left[\frac{N-m}{k} \right] k}$$

$(N-1)/\{int[(N-m)/k]k$ is a normalization factor and the average length is computed as

$$L(k) = \left[\sum_{i=1}^{K} L(i, k) \right] \Big/ k$$

This procedure is repeated k_{max} times for each *k* from 1 to k_{max}. This results in an array of mean values $L(k)$. Then, a least-square method is used to find the slope of the line that best fits the curve of $ln(L(k))$ versus $ln(1/k)$. That slope is the Higuchi Fractal Dimension. HFD is a scalar feature. It is noteworthy that the selection of k_{max} could strongly influence the results.

Fuzzy set theory was first introduced by Zadeh (1965). This theory renders classification flexible by allowing partial set membership rather than binary, 0 or 1, membership. The fuzzy function maps the membership degree of an element for a given set to a real value in between [0,1]. There are some feature selection methods based on the Partition generator function that comes from the fuzzy set idea.

This study is aimed at finding a simple approach with a low computational cost approach for discovering associations between clinical issues and modification of complexity of the neuronal activity. We expected to find the brain waves of healthy individuals to differ from gaming addicts. Therefore, the chaotic behavior of brain electrical activity was investigated through a time-domain analysis and extracting the fractal-like features of EEG signals. In line with our previous studies and to keep the approach simple and decrease the computation steps, we calculated the HFD for the total EEG signals (without focusing on any specific frequency band) was calculated (Roozbehi et al., 2020). Finally, the EEG signals obtained were classified based on these fractal-like features. We believe our research is more valuable as the COVID-19 lockdown has caused people to be at a higher risk of gaming addiction disorders.

Materials and Methods

Methodology and Research Design

This experimental case–control study was carried out on video game addicts and normal individuals living in Tehran. Thirty participants were recruited from 14 to 20 years old boys from two gaming centers using available sampling. To exclude individuals with any learning or mental disabilities, the experimental group was screened and all participants were interviewed by a qualified psychologist. Finally, 3 subjects were excluded due to their Symptom Checklist-90-Revised (SCL-90-R) scores while 7 others were excluded based on their Video game addiction test (VAT) scores. 20 participants were selected as addicted gamers. Twenty subjects were randomly selected from normal students aged 14 to 20. Eventually, two groups of 20 participants (addicted and normal) were formed. Ethical authorization for research was received through letter No. IR.TUMS.VCR. REC.1395.1562 from the Ethics Committee of the Vice-Chancellor of Research of Tehran University of Medical Sciences on January 29, 2017. The inclusion criteria for the study included males 14 to 20 years of age and the exclusion criteria included an SCL-90-R score higher than 1 and a VAT score less than 2.5. The following questionnaires were used as research tools:

The Symptom Checklist-90-Revised (SCL-90-R)

This questionnaire is a tool for the rapid assessment of subjects' mental pathology. It is a 90-item questionnaire assessing 9 psychological dimensions including physical complaints, obsession, and coercion, interpersonal sensitivity, depression, anxiety, aggression, phobic anxiety, paranoia, and psychosis. The validity and reliability of the Persian translation of this test were confirmed in Iran by Bagheri-yazdi et al. (1994) and its re-test reliability was ascertained at 0.97 within a week's interval. This test was taken by all participants via a trained psychologist in a clinical interview. Those scoring higher than 0.77 in each item were excluded from the test. The anxiety subscale was of special interest in exclusion as it may affect arousal activity and the brain's electrical activity. The mean ANX score was 0.44 ($\pm$ 0.24) for the control group, while the addicted group scored 0.48 ($\pm$ 0.22)—a seemingly insignificant difference.

Video Game Addiction Test (VAT)

There are several instruments to assess gaming addiction. Among the questionnaires designed to detect Internet and gaming addiction, the The Compulsive Internet Use Scale (CIUS) internet abuse questionnaire developed by Meerkerk
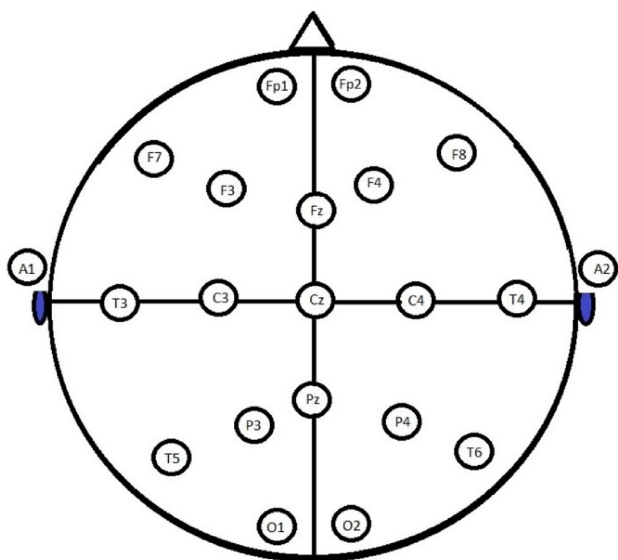
Fig. 1 Electrode positions for the 19-channel EEG apparatus

et al., Young's Internet Addiction Test, and Van Rooij's video game addiction test seemed most suited for use in this study (Meerkerk et al., 2009; Van Rooij & Prause, 2014; Van Rooij et al., 2011). However, the Van Rooij video game addiction test was the one finally employed since DSM-5 has introduced criteria to detect Internet addiction and Internet gaming: brain drain, withdrawal complications, compatibility (more time spent playing games), lack of control, loss of other interests, using despite negative consequences, temptation, changes in mood, loss of a job, relationship, or other important aspects of life and compatibility was not considered in the first two questionnaires (American Psychiatric Association, 2013). The validity and reliability of the translated version of this questionnaire were investigated in an article entitled "Psychometric Properties of the Persian Translation of the Video Gaming Addiction Test (VAT)" (Hosseini et al., 2019).

The subjects in both groups underwent EEG testing in three steps, each lasting 3 min. The test was performed using the 21-channel EEG system (Medicom; Russia, sampling rate: 256 Hz) by qualified personnel and according to guidelines of recording location and situations. The electrodes used consisted of Fp1, Fp2, F3, F4, C3, C4, P3, P4, O1, O2, F7, F8, T3, T4, T5, T6, FZ, CZ, PZ, and all electrodes amplitudes were evaluated relative to the earlobes (A1, A2) (Fig. 1). The recordings were taken between 9 and 13 o'clock, with each recording taking about 20 min, including preparation and cleanings. This experimental design included three parts; resting state, open eye state, and cognitive task. The working memory was selected for assessment, as the main target of the lesion in addiction. Based on prior studies, mental calculations and arithmetics are

related to working memory. As such, the working memory function is one of the main components of cognitive ability. In accordance with the literature on working memory and mental calculation and to reach a pure activation of working memory, here the visuospatial working memory and verbal working memory omission subvocal task was preferred. To achieve working memory function in arithmetics, a complex calculation is more preferable to a simpler one, because in a simple calculation the solution is retrieved from long-term memory instead of working memory. Another important factor in designing tasks and choosing a routine arithmetic fact[1] was removing the effect of expert and non-expert strategies in problem-solving, which leads to the activation of different brain areas.

In the first stage, each participant was asked to sit in a relaxed state and close his eyes. He was also asked to not think of anything and refrain from moving his body. In the second stage, he was asked to look at a point marked on the opposite wall without blinking and or moving. In the third stage, the participant was asked to act as he did in the second stage but to also count down by 3 s from 1000 mentally and as fast as possible.

Data Gathering

The final statistical population of this study comprised 40 subjects (20 addicts + 20 controls). All of the participants of the IGD group were between 14 and 20 years old, living in Tehran, and all right-handed (based on the Edinburgh Handedness Inventory). A clinical psychologist conducted all the diagnostic interviews for the primary assessments of participants.

As mentioned in the previous sections, DATA was recorded from the surface of the scalp of participants according to a standardized electrode placement scheme.

The next step was signal pre-processing. After that, data analysis was performed using a machine-learning approach. The machine learning perspective consists of five parts: (1) pre-processing; (2) feature extraction; (3) feature selection and dimensionality reduction; (4) classification; and (5) post-processing. In this study, we applied a machine learning approach and let the model filter the features. Therefore, the data obtained from all channels were used to extract and select the most relevant features.

The fractal dimensions were extracted using the HFD algorithm as the features which epitomize the obtained data. Moreover, feature selection was applied based on fuzzy set theory using the partition membership filtering technique and was used to select the subset of features. Supervised

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[1] An **arithmetic fact** is an operation on 2 whole numbers and the correct answer.

Table 1 The obtained results from the classifiers

Classified groups	Classifier	Total number		True positive		False positive		F-measure	
		Healthy	Addicted	Healthy	Addicted	Healthy	Addicted	Healthy	Addicted
Eyes-closed	MLP	20	17	20	17	0	0	1.000	1.000
	SVM	20	17	20	17	0	0	1.000	1.000
Eyes-open	MLP	17	18	15	17	2	1	0.909	0.919
	SVM	17	18	15	16	2	2	0.882	0.889
Cognitive task	MLP	17	18	16	18	1	0	0.970	0.973
	SVM	17	18	15	18	2	0	0.938	0.947

machine-learning classification using support vector machine (SVM) method was applied for feature selection. Waikato Environment for Knowledge Analysis (WEKA), a non-commercial and open-source data mining system was utilized for this purpose. To calculate these feature vectors for all instances, WEKA's PartitionMembershipFilter was employed, which can apply any partition generator to a given dataset.

Calculation

Signal preprocessing was performed on the recordings obtained from all 19 channels for each participant according to the following steps via EEGLAB v.2019:

(1) Artefact Detection and removal: EEGLAB was used to remove the artifacts of the recorded EEG signals. To this aim, from the "Tools" menu "Remove baseline" and "Reject data using Clean Raw data and ASR" options were used to remove artifacts.
(2) To remove out-of-band noise, the EEG time series were filtered within a range of 1–60 Hz using a Finite Impulse Response (FIR) filter.
(3) EEG Re-referencing: In this study, a common average referencing was used, i.e. the average of all channels.
(4) Line noise suppression was performed using a notch filter at 50 Hz.
(5) Bad channels or missing channels were repaired by replacing them with the average of all neighbors (interpolation).
(6) Ran ICA to detect components of each signal in each channel.
(7) Removed the components originated from undesired sources like electrocardiography (ECG) and electromyography (EMG) to prepare artifact-free EEG signals.

Results

During the preprocessing steps, some records were detected as being corrupted or disturbed; therefore, the final numbers of analyzed participants of different groups were as follows: Healthy and closed eye (Hec) = 20; Healthy and open eye (Heo) = 17; Healthy and calculation task (Hct) = 17; Addicted and closed eye (Aec) = 17; Addicted and open eye (Aeo) = 18; Addicted and calculation task (Act) = 18. After preprocessing, for each channel of each participant, a total of 44,700 records (equals 179 s) were kept. However, the HFD algorithms converted this series into two scalars. Therefore, we had 19*2 = 38 features for every participant.

The fractal dimensions were extracted via the HFD algorithm with $k_{max} = 8$. These features were filtered and combined through WEKA's Partition Membership method before using SVM and MLP as two salient methods of supervised machine learning algorithm and classification problems divide the participants into different classes. The results are displayed in Table 1.

The independent t-test used to compare two groups in each channel revealed meaningful differences 2 channels: the O2 channel (p.value$_b$ = 0.0339) in open-eye state and the F4 channel (p.value$_a$ = 0.027, p.value$_a$ = 0.006) in closed-eye state. Meaningful differences with two points level (0.05) found in another two channels: at P4 channel (p.value$_b$ = 0.0529) in closed-eye state and F3 channel (p.value$_b$ = 0.0524) in closed-eye state.

Discussion

Finding an appropriate method to recognize individuals addicted to gaming with neuroimaging devices is an important matter that eases the process of diagnosing the disorder and facilitates the treatment process. EEG is relatively low-cost, easy to use, and portable, making it is a very good fit for everyday clinical needs. Thus, in the current study, the brain waves and working memory of IGD individuals and normal people were compared. To this aim, QEEG data were obtained in 3 different situations and the Higuchi

complexity-measure and Partition Membership Filter were applied. Based on the analysis, it was possible to classify the participants with acceptable accuracy.

There are studies conducted to find a neurophysiological marker for IGD. Park et al. have proposed the heightened phasic synchrony in the gamma band during the resting state as a marker of IGD (Park et al., 2017). Son et al. suggest using lower absolute beta power as a potential trait marker for IGD (Son et al., 2015). In another study, Park et al. found significantly higher intrahemispheric fast-frequency coherence among IGD patients and proposed using it as a neurophysiological trait marker for these patients (Park et al., 2018). We tried to diagnose IGD based on the change in a complexity measure of whole QEEG data; as it is a more practical method and easier to use. Moreover, we find it a more reliable method as other suggested markers are not shown to be consistent.

When it comes to interpreting EEG data, researchers have a wide range of analytical tools at their disposal (Dauwels et al., 2010; Delorme & Makeig, 2004) and in recent years they have explored some new correlations between different measures of complexity (Cao & Slobounov, 2011; Dauwels et al., 2010; Sitt et al., 2014; Šušmáková & Krakovská, 2008; Weiss et al., 2011).

The fractal dimension (FD) of a signal is a measure for describing its complexity and self-similarity in the time domain. The fractal dimension of EEG was calculated using Higuchi's algorithm, which displayed the best result for EEG and other electrophysiological data. The Higuchi algorithm was run with the maximal 10 scales and $k_{max} = 8$ parameters. The Higuchi complexity-measure and Partition Membership Filter have proven a good method for diagnosing IGD simply and more accurately. According to Table 1, it has been shown with 95% accuracy that our finding is a good result for differing individuals with IGD and normal people.

Several resting-state EEG studies related to behavioral addiction have also been conducted. Lee et al. used EEG data to compare individuals having gambling disorders with normal people, in resting-state and open-eye states (Lee et al., 2017). Son et al., used the same method to compare individuals with IGD, AUD, and healthy controls (Son et al., 2015). Lee et al. conducted an eye open to eye closed comparison in another study to find patterns associated with comorbid depression in Internet addiction (Lee et al., 2014). We have used the same method but added recording during a cognitive task as other studies have reported alternation in the cognitive abilities of IGD patients (Batthyány et al., 2009; King et al., 2013; Peng & Liu, 2010). Moreover, we compared the complexity of brain waves in the three aforementioned states and observed the following differences:

(1) A significant difference in the opened-eye state at the O2 channel. This alternation of brain wave complexity in the right occipital region has not been previously reported in brain imaging studies.

(2) A significant difference in the closed-eye state in channel F4; Lin et al. had previously reported alpha band alternation in this channel in addicts (Lin et al., 2010).

(3) A nearly significant difference in the closed-eye state in channel P4. The P4 electrode was placed in the right Parietal and Angular gyri (BA39) and such alternation have been previously reported using fMRI in resting state.

(4) A nearly significant difference in the closed-eye state in channel F3; previously, Lin et al. had observed alpha band alternation in this channel in addicts (Lin et al., 2010).

The differences in P4 and O2 channels suggest asymmetrical differences in the right-sided parieto-occipital areas of the brain in gamers. The P4 area (right 39th Brodman) represents the right angular gyrus which is involved in visuospatial processing. Also, the O2 area (right 18th Brodman) illustrates the right side V2 area, involved in visuospatial information processing. It seems visuospatial processing (activation of the right parieto-occipital area) might be considered as an important neuro marker for gaming addiction.

Limitations

This research is a single-sex study due to the gaming centers in Iran accepting only male players, which can be considered as the limitations of the study. Also, the number of participants and their age range were limited. Moreover, observed differences in the delta pattern, potentially, indicate the early onset of learning disorders, to ensure the occurrence or absence of this complication in addicts people do not affect our results it is better to measure this issue with tests.

Machine-learning methods only show differences between pre-defined groups. They can not provide insights into the physiological mechanisms of the brain and reveal the causal interactions responsible for observations. For example, the complexity changes in the brain waves could be related to better 3-D rotating tasks after gaming. Thus, like other classification studies, this study only proposes that the complexity of the brain waves has changed due to gaming. Hence, it is important to design molecular biology studies to find out the details and reasons for the observations. On the other hand, a longitudinal study should be designed to assess the working memory before and after gaming addiction and find out the changes in brain waves in terms of time.

Conclusion

Brain waves are the result of the brain's neurodynamic processes. Hence, these changes in brain waves are the signs of a neurophysiological change in the brain. A combination of Higuchi complexity-measure and PartitionMembershipFilter can help classify IGD and normal participants with 95% accuracy as a simple and low-cost method that demonstrates the importance of the brain wave complexity as an EEG data feature. On the other hand, the findings of this study strongly indicate that gaming addiction, as a cognitive disorder, has associated brain wave alterations. Given the ongoing COVID-19 pandemic, people tend to stay more at home and, as such, are in more danger of gaming addiction disorders. Thus, an accurate investigation of cognitive disorders and gaming addiction is vital.

Summary

It is a reasonable hypothesis that the dynamics of EEG are inherently random and variations of complexity measures of these signals are either similar or reciprocal with time. To assess the effect of games on this complexity, an experimental case–control study was carried out on computer game addicts and normal individuals in Tehran. EEG data was obtained from each participant in both groups in three steps (resting state, open eye state, and cognitive task), each lasting minutes. The fractal dimensions were extracted using the HFD algorithm and the Partition Membership method. The extracted features were then filtered and combined to prepare the inputs of the support vector machine (SVM) and MLP classifier. Finally, without focusing on any special band, we found statistically significant changes in P4, F3, and F4 channels in the closed-eye state and the O2 channel in the open-eye state. The differences in the brain waves may indicate a pre-existing difference in the gamers' brains or a neurophysiological change in the brain as a result of playing 3-D games. Further research should be conducted to explore these findings.

Declarations

Conflict of interest We know of no conflicts of interest associated with this publication.

Consent to Participate Informed written consent had been obtained from all participants. The study was approved by the ethics committee of the Research Institute for Endocrine Sciences.

Consent for Publication As Corresponding Author, I confirm that the manuscript has been read and approved for submission by all the named authors. We declare that this manuscript is original, has not been published before, and is not currently being considered for publication elsewhere.

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