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BCI Tech in Gaming Training and Education

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Abstract

BCI as a technology has been developing relatively quickly in the past several decades. Numerous gadgets and devices have been presented on the market. Yet, if most of them are related to medicine and partly education, there are not as many which have to do with ultimate gaming. Of course, wearable devices constitute the sphere of medical data acquisition. However, none of them have to do with gaming education and training. This paper presents an overview of the existing BCI models focused on gaming. It suggests an experimental system justifying its necessity in the impact it would have on the gaming world. The utilization of BCI capabilities in developing a relatively new direction can change the sphere of gaming training altogether.

A. Introduction

Background

New technologies have been introduced into all spheres of human life - from touch-screen phones to advanced neuro-headsets that read the user's brain with high accuracy. Neurotechnology significantly affect a person's life and society, although their presence remains implicit. They include different technologies designed to improve and correct the brain's functioning and allow researchers and doctors to visualize brain activity. In general, neurotechnology will enable us to understand better how the brain functions and to study various aspects of a person's consciousness, mental training, and higher mental processes.

At the current level of development, neurotechnology are already being used in combination with virtual reality to provide better rehabilitation through simulations and immersions in certain situations. This situation is because, in a game form, a person learns, remembers, and perceives everything much better - therefore, games have been developed based on the principle that a person needs to control any of his indicators independently. Many patients in clinics using neurotechnology, because they cannot observe any changes in themselves, tend to stop exercising, whether in a state of concentration or relaxation. The user-controlled signals from the brain, which are necessary for progress in the game, are perceived much more positively and show better results than neurotechnology without involving such a method. It should be noted that in these developments, neurotechnology, as a rule, do not provide additional opportunities to the user. Therefore, the full potential of such a combination of technologies is not used. Using neurotechnology as an alternative way to interact with the virtual world, showing the patient or the player feedback signals, is very effective. This technology provides the sustained feedback needed for self-assessment or further psychological inference. This mechanism is not yet fully understood.

As already mentioned, in the form of a game, a person pumps his cognitive abilities better. It is necessary to understand how the human brain works in the condition of immense focus and stress when the individual is in the process of gaming.

Research Aims and Objectives

To use the BCI technology in monitoring the brain activity of pro-gamers (CS:GO, Dota, FIFA, etc.) with a subsequent recording of various parameters. This data is then recreated as a virtual trainer to be uploaded to the BCI gadgets for teaching novice players in the respective games.

Thesis

The BCI technology can potentially simplify the knowledge acquisition process through cognitive training.

B. Literature Review

BCI Technology Today

BCIs were created for use in the field of medicine: to restore the ability to move and help people with disabilities interact with the environment (Mk & Wolpaw, 2009; Zhang et al., 2019), rehabilitation after a stroke (Naros & Gharabaghi, 2015), communication with patients with isolation syndrome (locked-in syndrome) (Comaniciu & Najafizadeh, 2018). The positive experience with BCIs has prompted researchers to move beyond solving biomedical problems and start using them in other areas: neuroeconomics and neuromarketing, the games and entertainment industry, education, security, and law enforcement, as well as to improve cognitive functions (based on biofeedback technology) (Van Erp, Lotte, and Tangermann, 2012; Abdulkader, Atia and Mostafa, 2015).

The most common approach to implementing BCI systems is using electroencephalography (EEG) (Wang, Wang, and Jung, 2011; Gao et al., 2014). Recording the neurophysiological correlates of mental stress, concentration, relaxation, fatigue, or cognitive activity in real-time is a promising method for identifying a person's performance and involvement in learning activities (Ungureanu and Lupu, 2015). This method offers an advantage over the eye tracker (Asteriadis et al., 2009) and the tactile feedback method (Park et el., 2005) for obtaining information about a person's current state. Portable EEG technologies (PEEGT) make it possible to use BCI in non-laboratory conditions, particularly in training/education.

One of the promising vectors in BCI development is the study of the neuropsychological foundations of training, education, and human development. In this regard, it seems essential to introduce new methods that contribute to neurophysiological research in education. The relevance of using BCI in the educational process is due to continuous education (long-life learning) and the need for efficient and affordable automated learning systems (Van Erp, Lotte, and Tangermann, 2012). Neurocomputer interfaces are also a promising technology for implementing a strategy for individualizing learning: an intelligent system will be able to adapt to the activity of a particular user (Lance et al., 2012), adjust the presentation of educational material to his condition, help to concentrate or, conversely, relax when necessary, which should eventually lead to more effective assimilation of educational material. Finally, real-time tracking of neural activity expands the understanding of how the human brain adapts to different conditions, which can be used to develop new approaches to learning (Lance et al., 2012).

Today, brain-computer interfaces are mainly used in laboratory conditions, and only some of the above areas are beginning to test in the natural environment (Cinel, Valeriani, and Poli, 2019). BCI technologies are making their way into other markets. They can open up in the video game industry in entirely new ways. VR games are already available, where the interaction of a gamer with a fictional world does not require a keyboard or joystick (Stahlke et al., 2021). This requires non-invasive EEG headsets that read brain impulses: they are created by numerous companies available on the market today. The current trends demonstrate that the future lies with games that analyze the player's brain activity and change on the go, adjusting to one's preferences (Woźniak et al., 2021). And then the era of games will come, directly transmitting information to the brain. For now, however, the gamer's capabilities are severely limited by the physical body and cognitive abilities of the individual (Paszkiel et al., 2021). The real world will appear flat, colourless, and blurry compared to what one can create within the brain.

BCI Gadgets on the Market

A relatively large number of devices have appeared on the world electronics market capable of receiving various kinds of bioelectric signals from the human body, including electroencephalographic (EEG), and transmitting them to specialized devices (Paszkiel et al., 2021). An EEG uses electrodes attached to the head to read brain signals and record weak electrical nerve impulses created by a person's psychological state or thought process.

NeuroSky

One of the consumer-class neural interfaces on the world market is the neuro-headsets of the company NeuroSky (2022). NeuroSky interfaces are single-channel EEG interfaces. The company has suggested improving the field of neural interface applications via the introduction of specialized training complexes. Yet their systems have not yet been tested, and there is no open data on their efficiency. (NeuroSky, 2022) This gadget was explicitly created for schoolchildren and students. MindWave Mobile includes a range of applications ranging from casual games to fairly complex tutorials. The device measures brain activity and blink rate. Based on NeuroSky, one can create interesting creative projects - for example, a helmet that converts nerve impulses into sounds. Here one must also mention that the Neurocam camera is turned on only when the helmet sensors detect an increased concentration of attention on an object. In other words, the camera only records what the user is interested in (NeuroSky, 2022).

Emotiv EPOC Neuroheadset

The headset with 16 electrodes is compatible with computer interfaces (though only on Windows), can recognize up to 30 emotional states, and track the user's facial expressions (Emotiv, 2022). Emotiv's "brain" joystick can be used for more than just playing games or, not only controlling a virtual character. After some training and, accordingly, if one has the right software, one can use it to mentally control objects on the screen, change the image scale, change the shape of things, and so on (Emotiv, 2022).

Neuro controller MUSE

A compact electroencephalograph developed by the Canadian company InteraXon (2022) quickly reads brain signals. If you select the desired mode, the device sends signals that allow the user to relax, concentrate or create the desired mood, for example, the so-called "atmosphere of confidence." The most beautiful thing about this gadget is that, on its basis, volunteers reproduced the famous telepathic game from the book "The Hitchhiker's Guide to the Galaxy" (there, with the power of thought, you had to tilt the bottle to fill the opponent's glass) (InteraXon, 2022).

Kernel Helmet

Kernel continues to develop a headset for non-invasive optical brain scanning. The system is based on functional near-infrared spectroscopy, TD-fNIRS (Kernel, 2022). One can monitor the cerebral cortex's blood circulation (blood volume and oxygen saturation) and changes associated with nervous activity (Kernel, 2022). The method is not new, its development is based on the discoveries of the 1970-the 80s, but the equipment available for use in medical and scientific practice takes up a lot of space and is used only in stationary conditions. Kernel Flow should change the situation and replenish the arsenal of mobile means for monitoring body functions, following devices that monitor pulse, pressure, and temperature (Kernel, 2022). As an experiment, the FDA has already approved the use of Kernel Flow in a study of the effects on the human body of ketamine.

The hardware of the BCI Kernel helmet contains up to 52 modules installed on four plates placed on the head. The modules are equipped with laser sources that generate pulses less than 150 picoseconds wide and detector tubes with a diameter of 2 mm (Kernel, 2022). The assumed capabilities of Kernel Flow now match those of known stationary systems. However, developers have a lot of unsolved problems. Thus, the accuracy of measurements is affected by the hair's color and thickness. For the device's correct operation, it is essential to fine-tune the positioning of light sources and sensors; each helmet must be customized for each user (Kernel, 2022).

C. Suggested Methodology

The paper’s methodology is based on developing a proper BCI receiver with the necessary number of sensors for gathering data from pro-gamers. This information is then analyzed and categorized in terms of complexity. Novice gamers will be provided the training materials based on this feature. At the same time, the data received from pro-gamers will serve as a standard and an aim that those training will attempt to obtain. This data is sufficient for the experiment to continue, albeit it may be possible to shift the training camp from one location to another, which is safer.

D. Expected Results and Outcomes

Much of the research focuses on the role of BCI in monitoring and maintaining attention. The productivity of educational activity strongly depends on the degree and duration of the gamer’s focus and concentration. According to scholars, in the process of education/training, the level of attention demonstrates the tendency to decrease (Serrhini and Dargham, 2017), which requires the search for new solutions for its mobilization by the individual (Serrhini and Dargham, 2017). Neurocomputer interfaces are used as a mechanism for providing feedback (based on the registration of brain activity) to the individual (most often in the form of a sound signal) when the focus of their attention weakens in the process of mastering the specific skill (Lin et al., 2014; Sun and Yeh, 2017). Using this hint, with the help of self-regulation, the gamer can re-focus and change the flow of activity in time (take a break or switch to another action), ultimately leading to more productive outcomes (Mokhtar et al., 2017). At the same time, a signal about a decrease in the gamer's focus can be given to the separate individual and the trainer/monitor to control and correct the training flow (Chen & Wang, 2017). This kind of feedback can be based not only on monitoring the level of attention but on the appearance of negative or positive emotions during the training process (Lai et al., 2016, Huang et al., 2017).

The study on the level of focus and stability of the gamer's attention span with the help of BCI to adapt the presentation of the training manual to the cognitive activity of the individual takes place in a different context. First of all, we are interested in the dynamics of the attention span level in the training process following the pre-identified instructions from top gamers. This is all visual aid with an audio-visual follow-up with advice and steps to take for the individual to improve. Another area of research is devoted to monitoring the attention of gamers in connection with different levels of complexity and style of presentation of the pre-shot materials and video compilations of previous games. Yet the recordings vary in complexity for the trainee when the latter is immersed in the game while performing tasks of easy, medium, and high levels of complexity (Wang & Hsu, 2014); when studying video lectures of various types (Chen & Wu, 2015); in the perception of static, dynamic and mixed types of text (Chen & Lin, 2016); during discussion of the training session with the coach and trainer acknowledging one's performance in conditions of limited time (Ungureanu & Lupu, 2015).

Studying the attention span of gamers with the help of BCI covers the field of online remote training, and rarely does anyone turn to blended or traditional types of learning. This can be connected, on the one hand, with the possibility of more precise control over the content parameters (size, color, time of delivery of educational material, etc.), with which the individual works and the reaction to which is fixed by the BCI. On the other hand, the development of electronic technologies for training sessions and reliance on them in building the training process in the future dictate the conduct of such studies in the context of transferring educational information using BCI technology.

Neurocomputer interfaces also make it possible to analyze the level of the gamer's involvement in the training session (Andujar & Gilbert, 2013l Ghergulescu & Muntean, 2016). When it decreases, the system or the trainer/monitor takes timely action to renew interest. Portable EEG technologies are also used to monitor mental load and identify educational content, during the study of which it was maximum (Lin & Kao, 2018). In this case, the trainer/monitor has the opportunity to restructure the material to reduce the load and help students learn it better and faster.

In addition to information about the dynamics of cognitive processes in real-time, BCIs also read the gamer's emotional attitude to a situation or a specific impact (Verkijika & De Wet, 2015). Despite the difficulties associated with using special equipment in natural conditions, the introduction of psychophysiological methods into the actual learning process makes it possible to accurately determine the individual's mental state. For example, monitoring the level of the individual's stress using the BCI helps to identify the actions of the trainer/monitor, as well as some learning conditions (for example, time constraints) in which gamers experience a stress reaction (Verkijika & De Wet, 2015).

Taking into account the active interest of foreign researchers in introducing neurocomputer interfaces in the educational process, it can be assumed that this direction will remain relevant and promising in the coming decades. The number of studies on using BCI in education is still relatively small. This is because the infrastructure for forming relevant research areas is in its infancy, and the main focus is still shifted to the field of medicine and healthcare. Nevertheless, leading scientists draw attention to the fact that using BCI can benefit various areas of human life. At the same time, it is essential to overcome economic difficulties and systematize experimental and theoretical foundations and practical developments in building brain-computer interfaces.

The analysis of data retrieved from the required experiment will allow us to confirm that today there are two main directions for using BCI in the educational process:

1) identifying the characteristics of the current state of the student and organizing feedback for his timely self-correction (or correction with the help of a teacher) - the psychophysiological aspect;

2) monitoring the student's cognitive activity in the perception and assimilation of educational material in different contexts to determine the most optimal parameters and conditions for its presentation following the capabilities of each gamer.

Thus, in the first case, the emphasis is on changing the state or activity of the gamer, e.g., improving their gaming and level of training, and in the second - enhancing the training material itself. After all, when it is prepared with the help of pro-gamers, there is a chance of a better perception on the part of those trained later utilizing their knowledge.

Limitations

The main difficulties in the use of BCI in the training process discussed above relate to the technical requirements for the system and the process of human interaction with an electronic device: the optimal number and location of electrodes, calibration, a mutual adaptation of the user-computer, speed and quality of data measurement, software development, reliability of the "contact" with the brain, etc. (Wronkievicz, Larson, and Lee, 2015; Nakanishi, Wang, and Jung, 2016). A still unresolved issue is the classification of data read by BCI - the elimination of uncertainties associated with the nature of neurophysiological correlates of various mental phenomena. For example, this includes the problem of differentiating brain signals related to an effective response to a stimulus and auditory or visual attention or other cognitive processes that co-occur with it (Mühl et al., 2014). Therefore, the most accurate methods are required for classifying mental states, emotions, and cognitive activity based on EEG data to improve the interpretation of EEG signals associated with characteristic parameters of brain electrical activity (Lin & Kao, 2018). Solving these problems requires specific time and resource costs and the active cooperation of specialists in various fields. This is why multiple tests and test runs with pro-gamers wearing the system are a requirement for the success of this experiment

In addition to the above, it is necessary to highlight the difficulties specific to learning in natural conditions. An individual's mobility can lead to poor contact of the electrodes and, in turn, to errors in the measurements of brain signals (Nakanishi, Wang, and Jung, 2016). In addition, in natural conditions, a gamer is simultaneously affected by many factors, which complicates the processing of data obtained with the help of BCI. It also makes it difficult to draw conclusions on which impact a particular reaction was observed. For example, there may be discomfort from wearing the device itself, which in turn influences the reading of EEG signals. Therefore, it is essential to consider it in studies based on identifying negative emotions with the help of BCI since unpleasant experiences may not be associated with educational content but with a situation of prolonged equipment wearing (Nakanishi, Wang, and Jung, 2016). Thus, it is necessary to consider various factors to draw correct conclusions about what exactly influenced the change in mood.

Fatigue, which occurs in connection with the cognitive load in the learning process, reduces students' attention, affecting the amplitude of EEG signals. It is recommended to deal with this problem by optimizing the physical properties of the stimulus, in this case, optimizing the parameters of the presentation of educational material - it should not be too difficult to perceive (Mühl et al., 2014). In our opinion, not only taking into account the form of information submission will help reduce the level of fatigue. It is also possible to control the complexity of the training program for novice gamers (here, the zone of proximal development is more relevant than ever), take into account the effect of novelty, and select the optimal time for working with the task. To solve this problem in the natural training conditions, one should consider a complex of factors that can cause mental fatigue. Also, the quality of EEG signals can be affected by the need to distribute attention between the command that the user mentally or with the help of eye movement gives to the system and control over whether the system correctly executes it.

Controlling the mouse cursor through eye movements can increase the efficiency of human interaction with a computer and, in some situations, make it even faster than when using a computer mouse. For gaze-driven interfaces, the choice of an object on the screen is determined by the time the gaze was fixed on it (the residence time registration method). Longer than usual fixation of the gaze on the element increases the task's duration and causes the user discomfort. The difficulty also lies in the fact that when considering stimuli with an abundance of details, it is necessary to calculate the optimal time so that the person has time to study them properly, and the system does not consider the fixation of the gaze as a choice or intention (the moment of decision making). Thus, when solving complex learning problems, if the computer mistakenly activates any element (based on the fact that the user's gaze lingers on it, although the user looks at it or thinks about making a decision), this will inevitably increase the student's stress level and, respectively, will prevent him from concentrating on the task and learning the material. Attempts are being made to solve this problem using alternative methods of fixing visual commands based on selecting focal fixations or using hybrid interfaces (Zander et al., 2010). Another problem associated with controlling the system with the help of eye movement is the search for the optimal size of stimuli and the distance between them.

Despite the identified difficulties, BCIs open up additional opportunities in the field of education. For the visually and hearing impaired, it is possible to use vibrotactile neurocomputer interfaces (touch-based brain-computer interfaces) or non-contact ultrasonic tactile displays (airborne ultrasonic tactile display) in the learning process (Guger et al., 2021). The effect in the latter is achieved by stimulating skin receptors using focused ultrasound. The radiation pressure creates a tactile sensation on the skin's surface, which is how the human and the computer interact. Also promising are studies on the use of BCI to improve the social skills of students with autism spectrum disorders (White et al., 2016), the development of self-regulation of attention in students with ADHD (Lim et al., 2012; Ali & Puthusserypady, 2015), and the evaluation of therapy for children with cognitive impairments (Zammouri, Moussa, and Mebrouk, 2018).

E. Conclusion

Focusing on the tasks facing modern education (individualization of learning, development of students' self-organization and ability to reflect, continuous education, etc.), and based on the analysis of scientific sources, the following promising areas of application of neurocomputer interfaces in the training/educational process can be distinguished:

– The ability to predict the productivity of gamers' educational activities based on the data obtained with the help of BCI and pro gamers. When the concentration of attention deteriorates or the gamer experiences negative emotions, the learning outcome becomes worse. But in this case, we are talking not only about momentary feedback when a student interacts with specific content (reduced level of attention → giving a signal about this → suspension of learning activities to restore strength after fatigue). The data accumulated and analyzed by the system on the brain's activity in various learning situations can be used to identify the neurophysiological mechanisms underlying learning activity. This will make it possible to predict the potential success of the training sessions, as well as to identify difficulties (for example, a weak ability to hold attention to the object) and adjust the teaching methods taking into account individual characteristics.

- Teaching self-control (conscious monitoring of one's activity to detect errors promptly) using biological or neural feedback. Classes of this kind contribute to the development of self-regulation skills and reflection. In the future, the gamer will be able to be more attentive to changes in his condition and independently monitor them without system prompts.

- Identify the features of cognitive and affective states in real-time when teaching individual skills (precision in shooting, jumping, game movement, and overall gameplay flow, etc.). Educational activity in the development of various fields of knowledge has its characteristics. For example, different neurophysiological mechanisms are involved in processing numbers and words. There is also such a phenomenon as anxiety when studying mathematics (math anxiety), which negatively correlates with learning success. Determining the specific effects that affect mastering the material for each academic subject will also improve the learning process, making it practical and psychologically comfortable for students.

– Use of BCI as a method for assessing the impact of e-learning tools on the process of assimilation of information. Data on the use of BCI in education are somewhat contradictory. The variety of existing assessment tools, on the one hand, makes it possible for a comprehensive assessment, and on the other hand, it is predominantly subjective. Real-time recording of the pro-gamers neurophysiological reactions to educational content offered in electronic format can provide more objectified examination results.

- Measurement of the dynamics of the intensity of cognitive activity in the conditions of varied training tasks.

– Studying the effects of cognitive load in real-time in the classroom and identifying at the neurophysiological level the “threshold” of overload and the amount of information available for its successful processing to optimize the presentation of educational material and increase learning productivity.

According to the forecast of the development of neurotechnology in the future, a person can use applications in everyday life to monitor their current state, facilitate control over activities, increase productivity in decision-making and improve cognitive abilities. All these possibilities can also be used in solving educational problems. And although at the moment, additional research is required on using BCI in various fields of study. This review allows us to conclude that using brain-computer interfaces in the educational process is one of the promising areas for improving training effectiveness.

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