Towards a Direct Mental Based Decision Making: Electroencephalography (EEG) Case Study

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***Abstract*—Nowadays, there are several ways to interact with computers, applications, or even games. These ways vary between using a direct input via typical input mediums, automatic smart sensors, or even human postures. When dealing with people who suffer from disability, the aforementioned ways are not always applicable. In this paper, we introduce a new interaction style that helps disabled people. We focus on using a mental based decision making system. Precisely, we focus on issuing decisions directly from the electrical signals in a human brain. The goal is to transfer the interaction medium into the mental level. For the sake of clarity, we discuss a case study where we use a headset sensors to send direct Electroencephalography (EEG) signals as commands into the Tetris game. This case study is a simulation level suggested as a proof of concept. In the Tetris game the commands are discrete and limited. By preparing the Tetris game and using the Emotiv Epoc with a headset as the controlling tool. This paper provides a mechanism that grants ability for people to control and easily play computer games. This work designed with kind support from the King Abdullah II Design and Development Bureau (KADDB).**

***Index Terms*—Brian-computer interface, electroencephalography, sensors, DARPA, event-related potentials, learning process.**

I. Introduction

Everyday, there are many attractive achievements in the field of Artificial Intelligence (AI). The machine is able to deal with different data types, find a solution for new problems, and make life of people better in certain circumstances. One revolution in the AI field is neural network, which inspired by the biological neural networks in the human brain. Given a set of example data, the neural network tries to establish patterns that explain the relation between the input data and their related output [1] [2]. Such patterns can be used to predict the output for newly unseen examples [3]. Recently, there is noticeable attention to understand Electroencephalography (EEG), and explain their relation with several a human behaviors.

EEG signals are rich source of information that enable researchers to study how the brain order and control the whole body systems including joints movements. If we restrict our focus on how to train a smart unit to receive the brain EEG signals and convert them into a distinct and limited decisions that would be a reasonable progress in the field. Such enhancement opens the door for many sectors to benefit from this smart unit. For example, according to official statistics more than one billion (15%) people in the world live with some form of disability [4]. Pew Research Center (PRC) reported in 2003 that 19% of disabled people say that the disability problem makes using the computer difficult while 28% mentioned that the disability makes using computers impossible [5].

The global concept **Universal Usability** focuses on making products and items usable by all people. One of the main challenges is to accommodate individual differences among users, and this can be partially applied at a low level in computer games. In fact, a large portion of the available applied methods which are typical peripherals like (keyboard, mouse, etc.) exclude physically challenged computer users. For this reason, we intend our attention to develop a model that let those people with disability to use computers and games as same as normal people.

Recent years revealed a fast development in the Brain-Computer Interaction (BCI) devices and applications. Although the main paradigm for this development was oriented into the medical applications, a rapid rise in the game applications became very noticeable. A single BCI which is a direct communication path between the brain from one side and an external device from the other side is demonstrated to work as a simple mechanism for a user state measurement or for biofeedback. In games, BCI is one of the multiple inputs devices that can be used to control a game. This paper uses BCI to design and control the Tetris game and measures the player state and neurofeedback.

The brain wave which is a very low electrical signals produced by the brain, is described by the Electroencephalography (EEG) Which is Electrophysiological monitoring method to record electrical activity of the brain that is typically non-invasive. Both EEG and Electromyography (EMG) which is Electrodiagnostic medicine technique for evaluating and recording the electrical activity produced by skeletal muscles are used in this paper to get a direct input of the mental state of the player to control the Tetris game.

Over the last few years several new light and inexpensive devices, called Brain-Computer Interfaces (BCI), have appeared in the market [6]. Research on BCIs began in the 1970s at the University of California, Los Angeles (UCLA) under a grant from the National Science Foundation, followed by a contract from DARPA [7]–[9].

The BCI technologies have made it possible to read the brain waves and other electrical signals getting out from the Skull (e.g., EMG) at a low cost, less intrusive, and less invasive with no side effects [10]. The usability of the commercial EEG devices was tested in [11]. The signal from EEG has a very good temporal resolution [12], measurable in the range of milliseconds. However, EEG has a poor spatial resolution (in the range of centimeters) [13], and it is not easy to connect the underlying neuronal activities with a signal from a specific recording channel.

The **contribution** in this work is to develop a simple traditional Tetris game which is controlled by using BCIs technology. We use the EMOTIV EPOC to control the game objects as a new method of control. A specific headset is used to read both the EEG and EMG signals.

The paper is organized as follows. The related works are described in Section II. Section III presents the methodology. A detailed discussion about the proposed approach appears in Section IV. Finally, conclusions and future work are reviewed in Section V.

II. RELATED WORK

The work in [14] was the first research used a BCI with P300-ERPs modality to train and control a game. It describes three different approaches to control a Tetrislike game. The results show that Tetris V1 is effectively controlled with a few number of event repetitions. Tetris V2 requires more efforts to control which is mainly due to its high target probability. In the survey [15] the authors noted that the activity of the brain can be evoked because of three main reasons:

- The gamer is experiencing the game, the task and the interface, and gets, among others, frustrated, engaged, irritated, bored or stressed.
- External stimuli (visual, auditory, etc) consciously generated by the game to force the user to choose among certain possibilities or that occur in a more natural way because BCI recognizes that a gamer is interested in a particular event that happens during the game.
- The gamer consciously tries to evoke this activity by performing a mental task; e.g., imagining a movement or doing a mental calculations, leading to brain signals that can be recognized and transformed in such a way that the application is controlled by this imaginary movement.

In [16], the authors categorize the games into genres using their most prominent features. This is because some of the games could be considered hybrid genre games (games which cross genres, combining features not typically found together). **BCI in Games:** When it comes to brain-computer interfaces (BCI) and their use in video games, it can be hard to separate fiction from reality. In the latest series of Black Mirror [17] Charlie Brooker painted a terrifying portrayal of how BCI tech could develop. While it may seem far-fetched, however, here and now the technology is already proving its worth. While BCI games are not yet really an option for gaming consumers, they are already being used for a host of different projects, creating a whole new way of thinking about how we treat a variety of conditions.

In [18] Adams states that the main game genres fall into seven specific types; two of these genres have yet to be utilized in BCI games (sports and adventure games).

In [16], the authors noted that the BCIs are a weak replacement for traditional inputs and that there is a big gap needs to be bridged between games in research and commercial games.

The principal approach for categorizing BCI is to subdivide them into invasive and noninvasive [19]. Moreover, there are several types of neural mechanisms that can be used to control a game with EEG, namely neurofeedback. The neurofeedback is based on several EEG rhythms, P300 event-related potentials (ERP), and steady-state visual evoked potentials [14]. Some researches focus on using these neural mechanisms [20]. The research on brain activity does not focus on detecting anomalies that may indicate pathological changes, but on linking the recorded activity of the brain with the received stimuli, cognitive activities, progress in training various skills [21], and the degree of relaxation, etc.

III. METHODOLOGY

The EMOTIV EPOC+ headset [22] is a wireless headset provides 14 channels EEG, plus 2 reference channels. Saline-based wet sensors allow avoiding sticky gels. The headset is quite flexible, but its plastic structure limits the ability to adapt the device to untypical sizes or the shapes of the head. The signal is sent through Bluetooth or proprietary wireless communication. Battery life is up to 12 hours when using proprietary wireless, and up to 6 hours when using Bluetooth (see Fig. 1). An event-related potential (ERP) is the measured brain response that is the direct result of a specific sensory, cognitive, or motor event. More formally, it is any stereotyped electrophysiological response to a stimulus. The study of the brain in this way provides a noninvasive means of evaluating a brain functioning level.

Fig. 1: EMOTIV EPOC+ headset: The EEG channels record the Electroencephalography activity and pass them for further processing and analysis.

The presented work was developed on windows 10 and been tested on numerous players. We used the unity game engine, the C# as the programming language, and visual studio 2017 as the IDE integrated with the Emotiv API . Also we used the Emotiv cloud to save users data (e.g., the training profiles). The main reason for using the cloud instead of local database

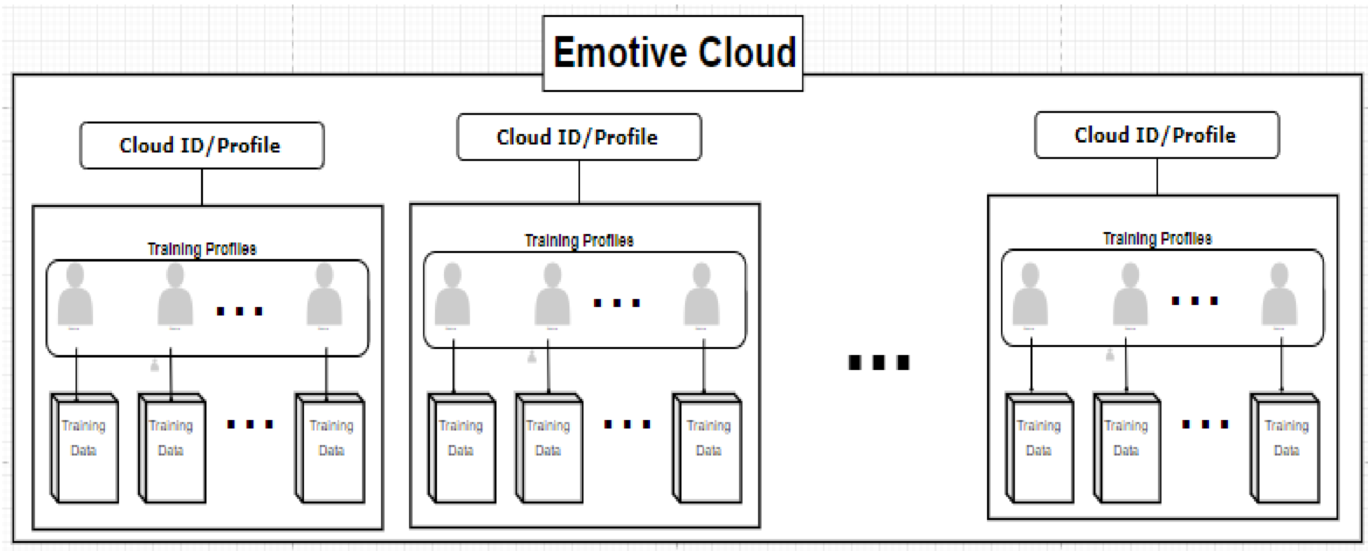

Fig. 2: Emotive cloud architecture. Each user has a separated profile including training data for that user.

is that the Emotiv cloud provides many features like saving records to the cloud storage, playback or export for analysis and share the EEG application data. We use it mainly as a way of login to add some restrictions on the game and test the code to cover the test cases. Fig. 2 shows the architecture of how we applied the registration using the cloud.

There are several types of neural mechanisms that can be used to control a game with EEG (e.g., P300 event-related potentials (ERP), and steady-state visual evoked potentials) [14]. The work in [20] uses these neural mechanisms. In the clinical applications, neurofeedback is frequently used in the form of game control. Games give an additional motivation to the trainees [23], which can be applied to all kind of users.

The work in this paper follows the (P300-ERPs) interaction and training modality since it is the most suitable for the task of the Tetris game. P300 represents a positive peak observed in the EEG that represents the cognitive processes of stimuli evaluation [12]. The characteristic of the P300 peak is that it is much larger for infrequently occurring stimulus categories than frequently occurring stimulus categories.

A. Sensors Distribution

With respect to the control paradigms, we must distinguish between three important brain areas; frontal, centro-parietal and occipital. In addition to these, we can also use the overall area covering from frontal to occipital.

The Epoc+ headset user is given a 14 sensors locations, and instructed to order them according to their preference. Each sensor should be placed on a specific position on the head. To enhance a sensor's signal quality and accuracy in an EEG recording, we placed the electrodes on the scalp according to the 10-20 system (see Fig. 3) introduced in [24]. Its name denotes the relative distances between electrodes (10 and 20 %) [25].

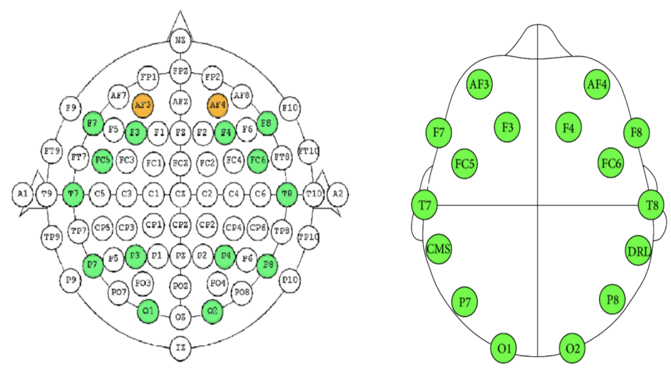

Fig. 3: The 10 - 20 system: The left side shows how Electroencephalography activity is distributed on the head. The right side shows the exact sensors locations on the head.

B. The System Flowchart

The processes sequence in the Tetris game is provided in the diagram presented in (Fig. 4) where the game starts after the headset is connected. Once the game start, the user has to login or create a training profile and start training the device, finally the engine containing the (Headset connection code) is passed through the game scenes to play the game. The training profile consists of data collected by EMOTIV EPOC+ headset while asking the used to follow a given instructions. Based on these collected data, several stages including signals filtering process, features extraction process, classification process, and decision making process are performed [26]. The core idea is to build a hypothesis that describes the relation between a given user behavior which is recorded in the user profile in the cloud and the taken decision which is decided in the given instructions during the training period. Such hypothesis can be used as the learning model which controls the taken decisions

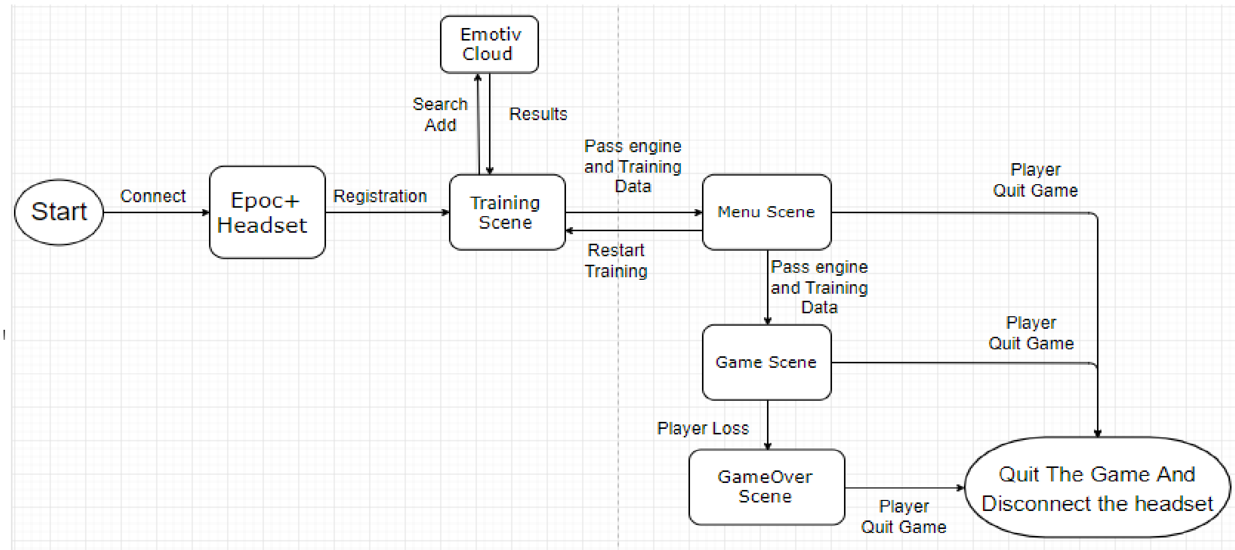

Fig. 4: The system flowchart: The steps describe the integration between the Epoc+ headset and the Tetris game. Also, the sequence of how Tetris is proceed in order to make the job done.

while the game is in the playing mode.

Fig. (5 - 6) show the process of executing EEG / EMG processes. In the the EEG execution mode, the process compares the trained data (i.e., precisely, the trained model or hypothesis from the training data profile) resulted from the training session with the brain wave currently read data by the EMOTIV EPOC+ device. If the generated decision (i.e., classified decision) for the current coming signals is neutral, then there is no action to do. If the generated decision is push, then push the Tetromino downward in the game working area. Finally, if the generated decision is rotate, then rotate the Tetromino clockwise. We can notice we have few discrete decisions (i.e., neutral, push, and rotate) can be generated automatically based on the coming signals. On the other hand, the EMG execution mode compares the universal signature (i.e., a universal trained model that can distinguish some specific muscles movements) to the brain muscles wave read by the EMOTIV EPOC+ device. If the generated decision is neutral, then do nothing. If the generated decision is blink, then resume/pause the Tetris game. If the generated decision is frown, then move the Tetromino to the right. Finally, if the generated decision is surprise, then move the Tetromino to the left.

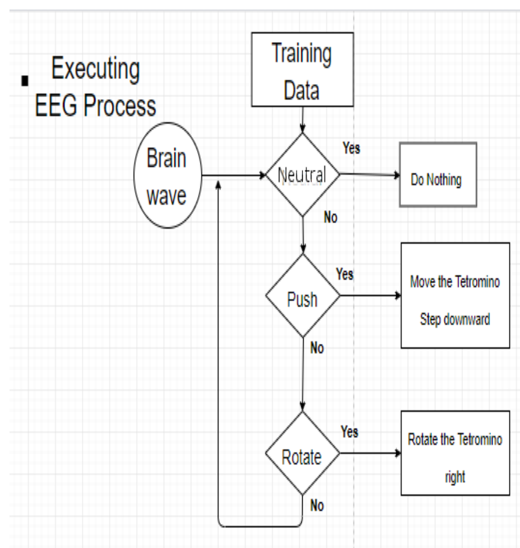

Fig. 5: Process sequences for the EEG mode.

IV. Discussion

The game consists of 4 scenes (training, main panel, game and end). These scenes can be divided into two main sections the panels (training, main panel and end) which are controlled by the mouse as an input device and the basic game (game scene) which is controlled by the Epoc+ headset. Our research focuses mainly on both of the training and game scenes.

In the training scene, the user login to his training profile and there are three training sessions: neutral, push and rotate. Each training session duration is 8 seconds, in which the user must be fully concentrated for the entire duration to record the EEG signals correctly and accurately. Moreover, the training sessions use the P300-ERPs mechanism in recording the EEG signals which also used to move the Tetrominos inside the game scene.

In the game scene, the user moves the Tetromino using both EEG and EMG. EEG used to rotate or push down the Tetrominos by comparing the stimulate from the brain waves with the built hypothesis or model during the training sessions. EMG used to move left, right or pause-resume the game by comparing the stimulate from skull muscles with the universal signature model stored in the API.

The developed game follows an adaptive approach, so the users gradually adapt to the game and increase their ability

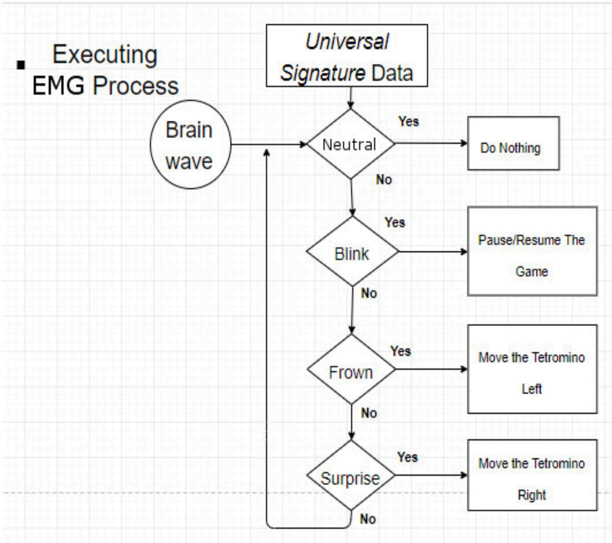

Fig. 6: Process sequences for EMG mode.

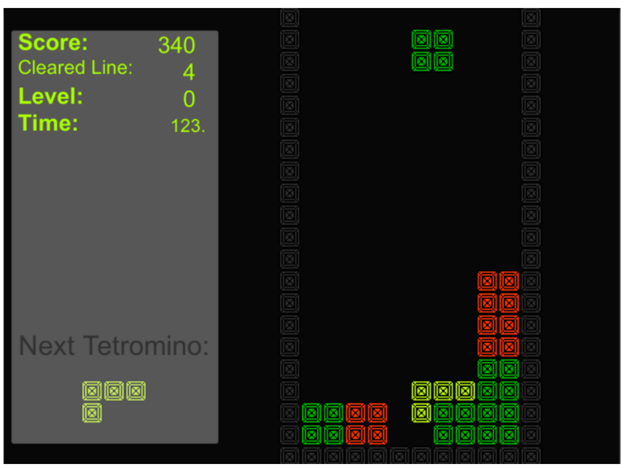

Fig. 7: Game Scene: The panel on the left screen includes many information about the current playing session; current score, number of cleared lines, current level, time since the current game session started and a preview for the next Tetrominos.

to control it. In this behavior, a specific Tetrominos falling from the top of the grid. The diversity and randomness of the falling Tetrominos increase as the player shows more progress in the game. More specifically, whenever the player clears more lines, the game starts to be more difficult and new Tetrominos shapes start to appear until the total number of Tetrominos diversity reaches to seven types. The order of the types adds to the falling Tetrominos (see Fig. 7) diversity as the player progress is as follows (the square Titromino, the line Titromino, the L Titromino, the J Titromino, the Z Titromino, the S Titromino, and finally the T Titromino).

Moreover, in order to measure the attention level of the Tetris players with the BCI, the speed of the falling Tetrominos is increased for each 10 lines cleared. Finally, an option is added were the player can train the device again during the game then back to play. This option is needed for new players which adds more flexibility to control the game.

V. Conclusions and Future Work

This work focuses on increasing the accessibility of persons with disabilities and ensure equal opportunities for them to enjoy and play games regardless of their disabilities. Thus, by developing the proposed Tetris game, the gate is opened for more development and research in the EEG brain signals field. The game was tested on several participants who were mainly divided into a first-time users and a skilled users.

When the game was tested, the Tetrominos fall in a specific manner diversity is strongly connected to the progress of the player in the game, the skilled players were very capable of controlling and clearing more lines and their ability to control increases the longer the duration they play the game. While the first-time players showed good ability to control the Tetrominos with low ability to clear more lines. Furthermore, their ability to control increases the duration they play the game.

When playing the game for long periods, the player's muscles are strained, which causes inaccuracies in the EMG signals reading, resulting in a reduced ability to control the Tetrominos, and in some cases the player needs to rest before continue playing.

In the future work, we focus on making the Tetris game with its two-part (menus and game) fully controlled by the EEG and EMG signals and give it the ability to connect to a different type of BCI and not only those who belong to the Emotiv company. Moreover, the research is open to incorporate the Epoc+ headset with robots [27] and several computer vision problems [29]. For more robust system, we will work on reading the raw data signals directly from the Epoc+ headset, so we can test different learning models.

References

[1] M. Al-Hami, M. Pietron, R. Casas, and M. Wielgosz, "Methodologies of compressing a stable performance convolutional neural networks in image classification," *Neural Processing Letters*, pp. 1–23, 2019.

[2] M. Al-Hami, M. Pietron, R. Casas, S. Hijazi, and P. Kaul, "Towards a stable quantized convolutional neural networks: An embedded perspective." in *ICAART (2)*, 2018, pp. 573–580.

[3] M. Al-Hami and R. Lakaemper, "Towards human pose semantic synthesis in 3d based on query keywords," in *International Conference on Computer Vision Theory and Applications*, vol. 2. Scitepress, 2015, pp. 420–427.

[4] W. H. Organization *et al.*, *World report on disability 2011*. World Health Organization, 2011.

[5] A. Lenhart, *The ever-shifting internet population: A new look at access and the digital divide*. Pew Internet & American Life Project, 2003.

[6] R. A. Connor, "Wearable and mobile brain computer interface (bci) device and method," Mar. 19 2019, uS Patent 10,234,942.

[7] J. J. Vidal, "Toward direct brain-computer communication," *Annual review of Biophysics and Bioengineering*, vol. 2, no. 1, pp. 157–180, 1973.

[8] J. J. J. J. Vidal, "Real-time detection of brain events in eeg," *Proceedings of the IEEE*, vol. 65, no. 5, pp. 633–641, 1977.

[9] M. Pacaux-Lemoine, L. Habib, and T. CarlsonS, "Human-robot cooperation through brain-computer interaction and emulated haptic supports," in *2018 IEEE International Conference on Industrial Technology (ICIT)*. IEEE, 2018, pp. 1973–1978.

[10] R. Spicer, J. Anglin, D. M. Krum, and S. Liew, “Reinvent: A low-cost, virtual reality brain-computer interface for severe stroke upper limb motor recovery,” in *2017 IEEE Virtual Reality (VR)*. IEEE, 2017, pp. 385–386.

[11] W. Hairston, K. W. Whitaker, A. J. Ries, J. M. Vettel, J. C. Bradford, S. E. Kerick, and K. McDowell, “Usability of four commercially-oriented eeg systems,” *Journal of neural engineering*, vol. 11, no. 4, p. 046018, 2014.

[12] M. M. Fouad, K. M. Amin, N. El-Bendary, and A. Hassanien, “Brain computer interface: A review,” in *Brain-Computer Interfaces*. Springer, 2015, pp. 3–30.

[13] A. A. Gaho, S. H. Musavi, M. A. Jatoi, and M. Shafiq, “Eeg signals based brain source localization approaches,” *INTERNATIONAL JOURNAL OF ADVANCED COMPUTER SCIENCE AND APPLICATIONS*, vol. 9, no. 9, pp. 253–261, 2018.

[14] G. Pires, M. Torres, N. Casaleiro, U. Nunes, and M. Castelo-Branco, “Playing tetris with non-invasive bci,” in *2011 IEEE 1st International Conference on Serious Games and Applications for Health (SeGAH)*. IEEE, 2011, pp. 1–6.

[15] A. A. Nijholt, “Bci for games: A Śstate of the artŠsurvey,” in *International Conference on Entertainment Computing*. Springer, 2008, pp. 225–228.

[16] D. Marshall, D. Coyle, S. Wilson, and M. Callaghan, “Games, gameplay, and bci: the state of the art,” *IEEE Transactions on Computational Intelligence and AI in Games*, vol. 5, no. 2, pp. 82–99, 2013.

[17] Black mirror series. [Online]. Available: https://en.wikipedia.org/wiki/Black_Mirror

[18] E. Adams, *Fundamentals of game design*. Pearson Education, 2014.

[19] T. W. Berger, J. K. Chapin, G. A. Gerhardt, D. J. McFarland, J. C. Principe, W. V. Soussou, D. M. Taylor, and P. Tresco, “International assessment of research and development in brain-computer interfaces. wtec panel report,” WORLD TECHNOLOGY EVALUATION CENTER INC BALTIMORE MD, Tech. Rep., 2007.

[20] B. Reuderink, “Games and brain-computer interfaces: The state of the art,” *WP2 BrainGain Deliverable, HMI, University of Twente (September 2008)*, pp. 1–11, 2008.

[21] S. Wolf, E. Brölz, D. Scholz, A. Ramos-Murguialday, P. Keune, M. Hautzinger, N. Birbaumer, and U. Strehl, “Winning the game: brain processes in expert, young elite and amateur table tennis players,” *Frontiers in behavioral neuroscience*, vol. 8, p. 370, 2014.

[22] Emotiv epoc+ specifications. [Online]. Available: https://www.emotiv.com/product/emotiv-epoc-14-channel-mobile-eeg/#tab-description

[23] A. T. Pope and O. S. Palsson, “Helping video games rewire" our minds",” 2001.

[24] G. H. Klem, H. O. Lüders, H. H. Jasper, and C. Elger, “The ten-twenty electrode system of the international federation,” *Electroencephalogr Clin Neurophysiol*, vol. 52, no. 3, pp. 3–6, 1999.

[25] V. Jurcak, D. Tsuzuki, and I. Dan, “10/20, 10/10, and 10/5 systems revisited: their validity as relative head-surface-based positioning systems,” *Neuroimage*, vol. 34, no. 4, pp. 1600–1611, 2007.

[26] R. Ramirez and Z. Vamvakousis, “Detecting emotion from eeg signals using the emotive epoc device,” in *International Conference on Brain Informatics*. Springer, 2012, pp. 175–184.

[27] M. Al-Hami and R. Lakaemper, “Sitting pose generation using genetic algorithm for nao humanoid robots,” in *2014 IEEE International Workshop on Advanced Robotics and its Social Impacts*. IEEE, 2014, pp. 137–142.

[28] M. Al-Hami, R. Lakaemper, M. Rawashdeh, and M. S. Hossain, “Camera localization for a human-pose in 3d space using a single 2d human-pose image with landmarks: a multimedia social network emerging demand,” *Multimedia Tools and Applications*, vol. 78, no. 3, pp. 3587–3608, 2019.