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An Introduction to BCI and Its Use in Video Games: A Review

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ABSTRACT

The input of a video game can vary from a keyboard, a mouse, a controller, and a plethora of other methods. The electroencephalogram (EEG) is a cap worn on the head that can detect electrical signals in the brain. This device is becoming seen as either an alternative to traditional controllers or a supplement. The EEG can be used with a computer to become a Brain Computer Interface (BCI), where a feedback loop is created between the game and direct signals from the brain. BCIs are increasingly being used for video games, whether for entertainment or serious purposes. In this paper, we review the components of a BCI and assess the general state of its use in video games. We describe the EEG, what inputs to measure, common preprocessing techniques, and different machine learning algorithms. We assess the game-making side, discussing the variety of games made. We conclude the paper by listing current limitations in different disciplines and point towards possible areas that need further innovation for the technology to become widespread.

Introduction

Traditional video games typically have the input of a keyboard and mouse to control specific actions within the game. Other inputs include gamepads and handheld controllers, or maybe even a steering wheel. All of these require hands to move or press down on components. A novel method of input that has been experimented on in the past decades had been using the raw electrical signals from a user's brain. The process includes decoding these signals using specific methods to completely bypass the appendages of the body. This effectively results in a user being able to control a game with their mind. Since the method of input doesn't require the user move, it can also be used as a supplement, rather than a replacement, for traditional methods. While the technology is somewhat new and has numerous limitations, this is a promising field that is able to exhibit the state of information transfer and decoding from the brain. This paper introduces the current state and terminology of the field, as well as what can be further studied.

Methods of Measuring

A large part of the process is first choosing an instrument with which to measure. The formal definition of a brain-computer interface (BCI) is a system that attempts to establish a direct channel of communication from the brain to an external computer, bypassing the natural channels of communication such as the peripheral nervous system (Blankertz et al., 2007). It creates a real-time looped interaction between the brain and the outside world. The output of the BCI influences the user's intention, which in turn influences the decoding of brain signals that makes up the output (Wolpaw, 2013). One part of the system is a device that captures neural activity through detecting the extraordinarily small electrical impulses of neural action potentials. Most of these are contained within the immediate area around the brain, but a small percentage can penetrate through to the scalp (Kuzovkin, 2011). This brings different ways of detecting these tiny electrical impulses, through devices that can be worn on your head or implanted through surgery, giving different types of BCIs with varying levels of advantages and disadvantages. The subcortical or cortical placement of micro-electrodes are able to offer the highest level of temporal resolution, which is the precision of measurement of the individual neurons. The problem is that they require invasive procedures and are not considered to be a good long term solution because there is the possibility of neural irritability, they have to be connected through a device that connects through the skull from the outside to the inside, and there's the possibility of the electrode degradation over time (Waldert et al., 2009). The safest procedure is an electroencephalogram (EEG), which is made up of electrodes placed on the scalp. This has the benefit of being convenient, cheap, and safer, but has the lowest level of temporal resolution, since it relies on the electrical signals penetrating the skull and scalp. It also mainly reads postsynaptic potentials, which are mainly sustained for around 100ms, instead of active potentials, which are weaker and only sustained for 1ms. (Kuzovkin, 2011). As a general rule, the more invasive procedure, the more accurate and the less noise it will have, while the safer the procedure, the less accurate with more noise (Rosenfeld & Wong, 2017).

An EEG measures the difference in electrical signals for different areas on the scalp. This means the need for "reference electrodes," where the electrodes in interest are compares to areas that are considered stable, such as the nose or ears, as well as the midline sagittal plane of the skull, where the corpus callous is, since the lack of neurons presents an opportunity to compare this baseline to other areas of activity. Electrodes are thus placed according to their area and their role and labeled accordingly (Kuzovkin, 2011). The frontal lobe is where decision making, future consequences of actions, and a myriad of other processes occur, and is labeled with the letter F. The temporal lobe includes auditory perception and long term memory and is labeled with the letter T. The central lobe, which is just the motor and somatosensory cortex, includes planning of motor functions and sense of touch, and is labeled with the letter C. The parietal lobe includes spatial perception and manipulation of subjects, labeled with the letter P. The occipital lobe is mainly visual processing and labeled with the letter O (Kuzovkin, 2011). This results in different electrode configurations, some like a 15-acquisition electrode system used in Peterson et al. (2020), and others like the configuration overlaid over the extended international 10-20 system used in Allison et al. (2012). A visual demonstration of the basic 10-20 system EEG is available in Figure 1.

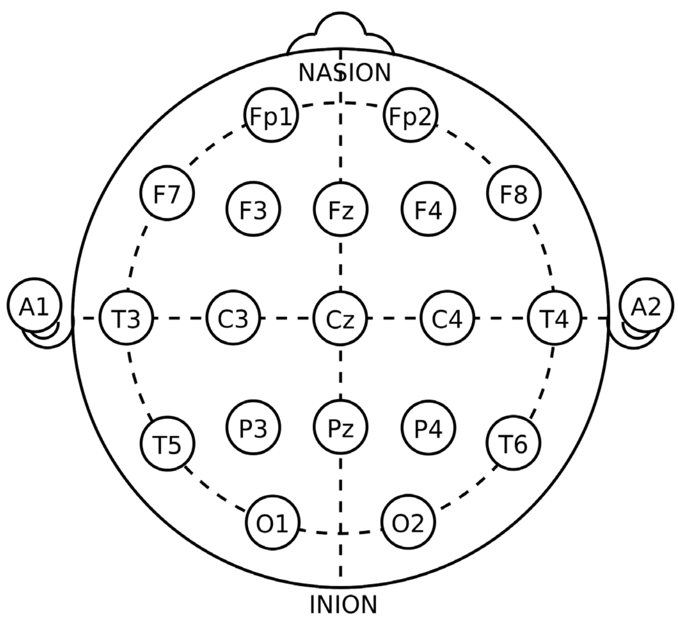

Figure 1. A diagram of the reduced 10-20 system for the EEG. *Note:* From *Electrode locations of International 10-20 system for EEG (electroencephalography) recording* by トマトン124, 2010, Wikimedia Commons, (https://commons.wikimedia.org/wiki/File:21_electrodes_of_International_10-20_system_for_EEG.svg). Public Domain.

The raw signals of the EEG can be classified in oscillations and gathered into ranges of frequencies. This includes the 1-4 Hz delta band, the 4-7 Hz theta band, the 8-13 Hz alpha band, the 8-13 Hz mu band, the 13-30 Hz beta band, and the 30+ Hz gamma band (Bordoloi et al., 2012). This forms one of three main "domains" that are basic level organizations of the raw data. These three domains are the time domain, the frequency domain, and the spatial domain. These plot time, frequency, or "space" (which is usually rendered 3D for visualization), against the number of "activations" of the neuron or their measured change in charge (Torres et al., 2020).

In addition to an EEG, sometimes other sensors are used that come from the peripheral nervous system (PNS). These include the electromyogram (EMG) and the galvanic skin response (GSR). These are useful as supplements that, depending on the task, can increase the accuracy of classifying different signals into their respective categories (Chanel et al., 2011).

Methods of Input

BCIs can use different types of inputs from different regions of the brain and with different frequencies. One type of EEG signal is called motor imagery (MI). This originates from the sensorimotor region of the contralateral and ipsilateral hemispheres and relates the mu and beta rhythm bands, which are either suppressed or promoted (Tangermann et al., 2008). MI can be generated through imagining body parts and moving them, where the user is instructed not to actually move, since such movement would induce noise to the EEG. The typical limbs that subjects are asked to imagine usually depends on the cortical homunculus, where certain parts are weighted more than others, e.g. hands, tongue, and lips are extremely prominent. Huang et al. (2012) uses MI detection for control of a wheelchair in a 2D game. While MI has seen extensive use in the treatment of motor impaired people, it also has use in other types of BCIs (Kerous et al., 2017).

While MI is a type of endogenous BCI, single state visually evoked potential (SSVEP) is exogenous. SSVEP is a type of evoked potential (EP), which is a type of event-related potential (ERP). Essentially, it is a response to a specific constant visual stimulus, a light blinking at a constant frequency. This can be used so that if a subject looks at some light blinking at a frequency of some amount of hertz, an action happens in a program (Wang et al., 2010). On a monitor, for instance, a spaceship can be tilted and fired by the subject looking at different parts of the spaceship blinking at different frequencies, as in Martišius & Damaševičius (2016), or control a cursor such as in Allison et al. (2012). On a monitor, limitations exist depending on the refresh rate of the monitor. The refresh rate must be some multiple of the blinking stimulus and not be harmonic with another used stimulus. For example, for a 60 Hz monitor, 6.67 Hz, 7.5 Hz, 12 Hz, 15 Hz, and 20 Hz are available, but 7.5 and 15 Hz for example cannot be used together (Martišius & Damaševičius, 2016). One problem with this approach is that it requires external setup along with the BCI. SSVEP is generally resistant to typical artifacts such as blinking or moving that can make classification more difficult. In addition, there is a simple extraction of desirable features, as all that is needed is to focus of the frequency components (Lalor et al., 2005).

Another method is the P300 potential, a type of paradigm that is an EP. It is a voltage alteration locked to a specific external event, appearing some 300-500ms after the event (Fouad, 2021). This is a type of oddball paradigm, a type of method derived from presenting a subject with the same stimulus except one "oddball" to differentiate it. A distinction can be made within the P300, the P3a and P3b, where the P3a is associated with attention-based novelty and the P3b is associated with updating working memory when their is a deviance after a given stimulus (Schlüter & Bermeitinger, 2017).

Preprocessing Techniques

Before capturing the data, preprocessing can start. A band-pass filter is designed to optimally reject unwanted frequencies while also having a flat uniform frequency in the passband. A notch filter can also be used to filter out a specific frequency, such some interference from a power line or other external noise (Torres et al., 2020). In Kato et al. (2018), a 3-70 Hz fourth-order Butterworth band pass filter and 50 Hz notch filter was used to isolate the data to get rid of any external noise. With this, they were able to robustly compare three different processing methods using a lock in amplifier with the goal of preventing feedback delay.

There are multiple ways to analyze EEG data. These include analyzing the time domain, the frequency domain, the spatial domain, and multiway processing. The time domain is typically used as it is the easiest, but methods such as a Fourier transform allow frequency domains to analyzed, and methods such as visual maps allow the spatial domain to be analyzed (Sanei & Chambers 2021). To extract features and continue to process the data for the machine learning algorithm to read, features must be identified in one of these domains.

Many artifacts still exist in the data, even after applying the previous methods. These can include eye blinks and other muscle movement, which give off small electrical signals of their own. The detection and removal of these artifacts is a large challenge for EEG analysis. Balance must be met between a large amount of features being extracted, while maintaining low artifacts and minimal computation (Vaid et al., 2015). Independent component analysis (ICA) is often used to remove EEG artifacts, as it was designed to isolate a specific aspect of a larger noise, such as a single voice in a crowd (Hu & Zhang, 2019). ICA also has the benefit of separating P3a and P3b. In contrast, principal component analysis (PCA) does not (Debener et al., 2004). ICA ultimately holds more promise for multidimensional biomedical signals such as the EEG. It does not lose information when losing dimensionality compared to PCA, and has the aforementioned benefits (Bugli & Lambert, 2007). Since its inception as an extension of PCA as reported by Comon et al. (1992), it has cemented itself as having an important use in EEG signal analysis.

Common spatial patterns (CSP) is a great method for a subject specific spatial filtering, specifically with motor imagery. There are variations on the original algorithm such as Common Sparse Spectral Spatial Patterns (CSSSP) (Dornhege et al., 2006) and Robust Common Spatial Patterns (RCSP) (Yong et al., 2008). Research that includes CSP includes Martišius & Damaševičius (2016) and Coyle et al. (2011). Surface Laplacian derivation (SLD) is another method useful in MI that improves the localization of sources. This means that classifiers are able to better distinguish the difference between spatial motor tasks, as they have a starker difference (Huang et al., 2012).

The techniques listed are only a small subset of the numerous algorithms commonly used. Even for those not commonly used, they can be extremely effective when used in the right circumstances. For further reading, Cabañero-Gómez et al. (2018) describes the state of EEG signal analysis when using video games. For a more in-depth analysis, see chapter four of Sanei & Chambers, (2021).

Machine Learning Algorithms

After the features are processed and picked, they are "classified" using a machine learning algorithm. Traditionally, the data is split into pieces, where algorithm "trains" on one portion of the data, then uses the other portion to test the performance while not actively training the model. One way this is executed is called k-fold cross-validation, where the entire data is split into k equally sized partitions, then k-1 subsamples are used for training, then the remaining sample is tested for validation. The process is then repeated k times where the validation and training samples change until all subsamples have been used for validation (Refaeilzadeh et al., 2009). This is done in order to flag problems like selection bias and overfitting, which is when a model "overreacts" to classifying a certain set of data, making generalization to other other models difficult or impossible. It can be pictured similar to a scatter plot with a positive correlation, but instead of fitting it generally to a line, the data is fit perfectly to some large order polynomial. In Martišius & Damaševičius (2016), for instance, 10-fold cross validation was used on two subjects in order to evaluate a classification model on a prototyped BCI video game system using SSVEP.

One algorithm that is commonly used to analyze EEG signals is called support vector machine (SVM). This algorithm is a binary classification algorithm that attempts to create a linear separation between two groups of datapoints. It optimizes this separation by placing itself farthest away from the closest datapoints, trying to maximize the magnitude of the vector originating from the datapoints to the separator (Cortes & Vapnik, 1995). This can extend into three dimensions with a two-dimensional plane separating groups, and into further dimensions by using hyperplanes (Kuzovkin, 2011). Different "kernels" other than linear kernels also exist to classify the data shape differently and more accurately. Data first must be processed to create the separation of groups before the SVM is used, creating numerous preprocessing and feature extraction methods. Chanel et al. (2011) uses three classifiers, with SVM being one of them.

The algorithm Linear Discriminant Analysis (LDA) is also commonly used. The fundamental concept for LDA is optimizing a line so that points in a two-dimensional space, when collapsed onto some one-dimensional line, are separated as much as possible (Xanthopoulos et al., 2012). LDA is usually used for low dimensionality problems since there are multiple challenges to overcome when dealing with higher dimensions. While there are methods, it is still a developing field with further advancement available (Mai, 2013). For a rigorous mathematical explanation, Izenman, (2013) demonstrates the process with an example. In the realm of BCI research, Scherer et al. (2008) uses an LDA set up in three pairwise configurations for a multi-classification problem, since LDA is best used to classify two classes.

Another algorithm used to analyze EEG signals is a convolutional neural network (CNN), seen in Figure 2. A CNN is a type of deep learning (DL) network which exhibits excellent performance in medical applications and is beginning to be tested in BCI applications. It can take in either raw EEG input or extracted features (Liu et al., 2020). The CNN takes in an input, then performs a series of "convolutions" and "pooling" with some size kernel before the fully connected layer (FC).

- A convolution is a mathematical operation that produces an output that expresses how one function is modified by the other (Albawi et al., 2017). This is repeated across the input for a specific kernel size, for instance 5x5, then takes a 5x5 slice of the input to create a 1x1 slice of the output. This is repeated so a full output is created with the same dimensionality of the input. Utility-wise, this is used to emphasize certain features. In an image, the edges are commonly emphasized.
- Pooling is a method to reduce the dimension of the data, and is typically used through either max or average pooling. For some kernel size and type, for example "2x2 max", the maximum of a 2x2 slice is taken and output into a 1x1 slice of the output (O'Shea & Nash, 2015). Unlike convolutions, this doesn't overlap, giving a loss in dimensionality, which is needed for the next step.
- Convolutions and pooling are repeated until the slices are feasibly small enough to be fed into the FC layer, which is just a neural network (NN). If it wasn't small enough, the neural network would be too big to feasibly train. The NN uses weights and balances to establish a relationship between a set of inputs and an output. With the reduced dimensionality of the data and a greater amount of significance to the datapoints, the FC layer is able to better connect the data. Further reading on how a neural network is created is available in Shanmuganathan (2016).

In BCI literature, Li et al. (2021) uses type of CNN, proposing a simple-Bayesian Convolutional Neural Network (SBCNN) to detect a P300 visual stimulation paradigm.

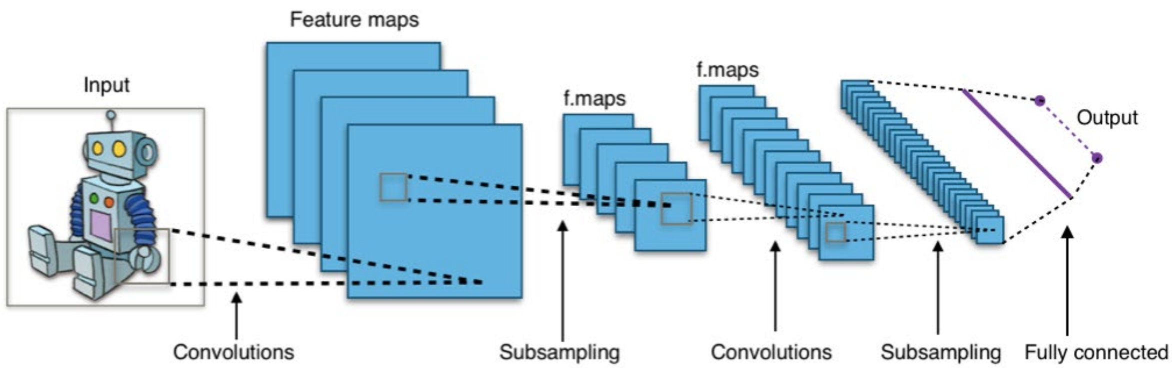

Figure 2. A layout of a typical convolutional neural network. This includes the convolutions, the pooling, called subsampling here, and the fully connected layer. *Note:* From *Typical cnn* by Aphex34, 2015, Wikimedia Commons, (https://commons.wikimedia.org/wiki/File:Typical_cnn.png). CC BY-SA 4.0.

Games

Many small video games have been made in order to test a BCI paradigm. Examples of video games include pinball in Tangermann et al. (2008) and a spaceship game in Coyle et al. (2011). Pires et al. (2011) uses Tetris to make a comparison between P300 and MI. Bradberry et al. (2011) doesn't specifically use a game in its full definition, but experiments with cursor control, a prominent aspect of most games. In Li et al. (2021), a novel game called MindGomoku, based on the strategy game Gomuku that uses Go pieces, is proposed and tested. Scherer et al. (2008) demonstrates a simple coin collection game in a three-dimensional environment. With a more practical application, Huang et al. (2012) demonstrates a virtual wheelchair control simulator.

Virtual reality (VR) games are typically considered to be an immersive technology. There are not a large number of VR BCI games, however. Besides a possible increase in immersion, there is not much else in terms of benefits. The performance of the classification does not change between an abstract feedback, and more realistic (Vourvopoulos & Bermúdez i Badia, 2016; Neuper et al., 2009). A possible reason to the lack of VR BCI video games is the easier nature of creating small form flatscreen video games, which are needed for time and resource efficient research studies. Another reason could be the cumbersome nature of VR headsets, especially in relation to its conflict on the head with EEGs. VR is mostly considered in a rehabilitative nature, seen in Wen et al. (2020).

In the realm of BCIs being a supplement to video games, some work has been done. Chanel et al. (2011) evaluates using an EEG to determine how difficult a game is to the user, which resulted in low classification accuracy. The goal of this would be a method of increasing or decreasing a game's difficulty automatically so the user can receive the most enjoyment and be the most challenged. Berta et al. (2013) similarly assesses using an EEG to gauge a user's "flow," achieving low training time but also a relatively low accuracy.

Various tools have also been developed to help design video games with BCIs. One such tool is to do with virtual environments and named OpenViBE, a free and open-source software developed and described in Renard et al. (2010). This software allows the researcher to use a toolset to visualize feedback and even design a BCI without knowing how to write code. It includes high modularity and tools for users of all types. As it is open source, its is also being continually improved to this day. OpenBCI is also a great website for community help in terms of general BCI setup ("OpenBCI Home Page"). Traditional game engines can also be used to create BCI games, although it must have some scripting capability in something like C++ or python to be able to interface with the EEG (Wang et al., 2011).

BCI video games are also not strictly limited to entertainment purposes. These alternate types of games used for treatment or training are dubbed "serious games" (Zheng et al., 2021). These serious games can help people with mental health disorders like ADHD or autism to treat patients with low side effects. Specifically for autism Mercado et al. (2021) found that using a simple BCI video game called FarmKeeper, subjects were able to display a small increase in attention capacity. In Ali & Puthusserypady (2015) a 2D BCI video game was compared to 3D versions with varying noise using healthy subjects, showing potential for possible experimentation for subjects with ADHD. The efficacy of these serious games has been debated, however, in Coenen et al. (2020), where only a marginal increase, or no increase at all, was found supporting in the claims of increased relaxation or concentration.

Limitations and Further Work

There are numerous limitations with BCI video games. A large part is hardware. EEGs are limited by a low transfer rate compared to traditional keyboard and mouse interfaces. They are also cumbersome to prepare, set up, and use in addition to being expensive (Cattan, 2021). The price of consumer EEGs has started to decline, but not enough for it to become a common household item, since 16 electrode headsets have been found to be acquired for less than 300 Euros (Lécuyer, 2016). Peterson et al. (2020) investigates the usability of a low-cost headset and finds that, with proper noise reduction, it becomes a possible alternative, albeit with some technical drawbacks, such as a lack of a license for medical use. Most EEG headsets also rely on a wet applicative to increase electrical conductance with the scalp. Dry alternatives have been investigated (Liao et al., 2012; Shad et al., 2020; Mathewson et al., 2016) and found to be a possible alternative. Various materials have been found to possess qualities that could have the same effectiveness as wet electrodes, and dry electrodes can be more effective when worn for extensive periods of time (Liao et al., 2012). The innovation of the EEG is steadily advancing, but more work needs to be done before it can be within consumer use. The development of an alternative, convenient, non-invasive method is also a possibility.

On the side of the subjects, problems include the variability of performance using data within and across subjects, as well as the concept of BCI illiteracy, when a person is "illiterate" to a specific type of BCI such as MI and thus unable to use it (Martišius & Damaševičius, 2016). In fact, MI seems to be the most prominent method of BCI illiteracy when compared to SSVEP or ERP (Lee et al., 2019). The concept of BCI illiteracy has also been critiqued as a method that could cause researchers to misattribute potential experimental design error to a static attribute of a person. There can be multiple other causes of poor performance and framing it in exact terms can be problematic (Thompson, 2018). Another problem relative to subjects is that many experiments make subjects tired with excessive and repetitive audiovisual stimulation when collecting data (Baek et al., 2020). Consistency and standardization is currently lacking with regards to the treatment of subjects, which results in varying data and conclusions.

Regarding neuroscience, more signals need to be discovered, and more importantly, they need to be easily classifiable and useful (Lécuyer, 2016). There are also ethical aspects to BCIs that need to be considered, such as psychological effects, common practice, and policymaking (Coin et al., 2020).

The video game design for many of these studies is also poor. A large reason for this is due to the nature of research forcing results quickly. Another part is the lack of collaboration with game developers and other cross-disciplinary professionals. The researchers coding these games are usually not familiar with game design, holding a higher skill in EEG signal analysis or algorithmic engineering.

Conclusion

In this paper we describe the methods of creating a BCI, the current state of games using BCI, and the current limitations and paths for further innovation. We introduced the terminology used in the field and stated further reading for a greater understanding. For the creation of a BCI, we described the optimal measuring device, different methods of experimental setup, common methods of preprocessing data, and common machine learning algorithms to classify the data. We discuss the use of BCI in video games and its current problems and possible solutions or areas of improvement. This paper serves mainly to introduce the field and create a path of gaining the knowledge to then pursue innovation in the right direction.

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