An Overview of Brain Computer Interfaces

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Abstract

This paper presents an overview of the research and development of Brain Computer Interfaces (BCIs), focused mainly on the software component. A classification of BCIs is proposed, providing a general sense of the various ways one can approach such systems. The different types of BCI systems are the main focus of the paper, and related research and development efforts are explored. The proposed classification is based on several major characteristics of BCIs: independent versus dependent, invasive versus non-invasive, and exogenous versus endogenous. Issues and limitations currently faced by BCI researchers and developers as well as several existing BCI applications are also surveyed. In addition, directions of future work pertaining to BCIs are briefly discussed.

1 Introduction

Advances in Human Computer Interaction (HCI) continue to play an important role in society. One growing development in HCI is the concept of a direct Brain Computer Interface (BCI). The goal of BCI is to improve the quality of one's life, and its full potential has been yet to be explored. Much of the research so far mainly focused on people with severe motor disabilities, but BCIs also have potential in the domain of immersive video games, communication, and robotics. However, many challenges arise in the development of such systems. The main factors that affect the performance of a BCI system include the type of brain signals used as data, data acquisition methods, the algorithms that are used to translate the obtained data, the hardware that facilitates user control, the type of feedback the user receives when executing commands, and the characteristics of the users themselves. Therefore, future improvements in BCI systems require structured, well-controlled studies that evaluate and compare alternative and combinations of signals, various data acquisition methods, alternative translation algorithms, and various control applications offered to different users.

Unfortunately, most current BCI systems do not readily support such structured research and development [1]. Though many have tried to accomplish this (e.g., [2], [3]), up to now BCI research has only offered previews of the lackluster capabilities of current BCI systems. So far, there only exist demonstrations of systems that one or few users can control a certain device if a certain brain signal is recorded and measured in a specific way, and translated into control commands by a certain algorithm [4]. These systems are still unable to fully unleash the true capabilities of BCI, which might be achieved by utilizing and comparing various brain signals and processing methods. By demonstrating the impressive capabilities of this yet underrated form of interaction through innovation, a more immersive means to operate this technology could be achieved. This is important because through immersion, not only can BCI boost the standard of living, the bulk our society's unyielding mindset towards operating such new technology may also improve. Therefore, further progress in BCI research and development is needed.

This paper aims to provide an overview of the research and development of BCIs. In Section 2, we propose and describe our taxonomy of BCI systems, breaking them down into three main categories: independent and dependent, invasive and noninvasive, and endogenous and exogenous. In Section 3, the development of BCI systems is explored. In Section 4, we present existing applications created as a result of BCI research. In Section 5, we discuss the surveyed research and development. Finally, in Section 6, we provide our concluding statements, and discuss the directions of future work BCI has to offer.

2 Proposed Classification

BCI development is traditionally divided into several categories: independent or dependent, invasive or noninvasive, and exogenous or endogenous. Figure 1 illustrates our suggested taxonomy on BCI development, presenting the various types of current BCI that fit into their respective categories.

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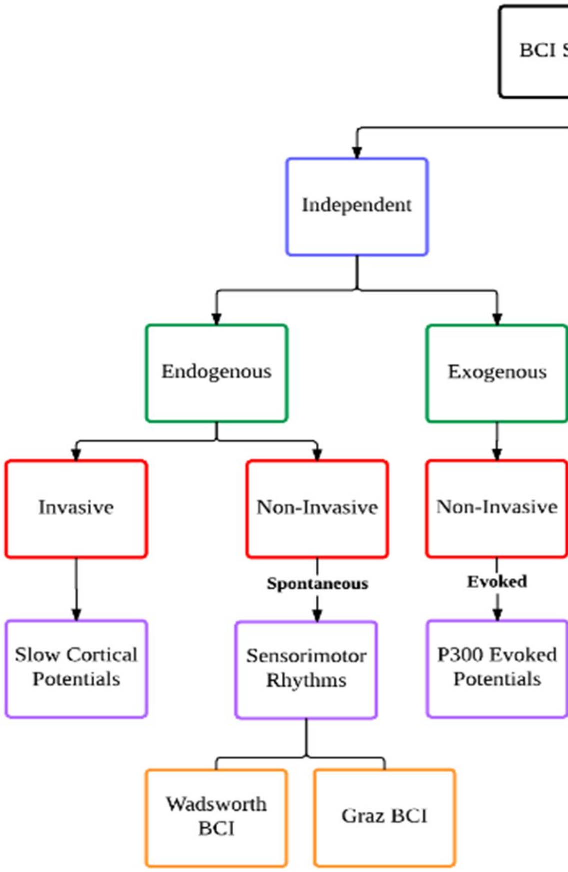

Figure 1: Abstract taxonomy of BCI development

Independent vs. Dependent

Independent and dependent BCI systems are distinguished by how reliant the system is on additional types of activity in order to function. An independent BCI does not depend on the brain's pathways (i.e., peripheral nerves or muscles); activity in such brain output is unnecessary to create the brain activity (e.g. EEG) required to execute a certain command [4]. For example, a user can choose a specific letter by solely thinking about it. In the BCI system described by Farewell and Donchin, the user is presented a matrix of sequentially flashing letters [5], [6]. As the letters flash, the user produces a P300 potential, allowing for the user to select the currently lit letter. It should be noted that the generation of the appropriate signals depends on the user's intent instead of the direction of the user's gaze. Instead of relying on such peripheral nerves, independent BCIs provide the brain with a new communication path, which could be more useful and theoretically interesting than dependent BCIs. In addition, independent BCIs may deem useful towards those with severe neuromuscular disabilities.

In contrast to independent, dependent BCIs use the activity in the brain's normal output pathways to generate the brain the brain activity (e.g. EEG) required for the system to function. Similar to the previously mentioned system for independent BCI, Sutter described a dependent BCI system that also presents the user with a matrix of sequentially flashing letters [7]. However, with this system, the user was able to select a specific letter by looking at it. As the user looks directly at the flashing letters, his/her visual evoked potential (VEP) was recorded over the visual cortex for each flashing letter; the largest recorded potential determined the user's selected letter. In this system, the EEG component of the brain is used to carry out its task, but the signal is generated through the direction of the user's gaze.

Invasive vs. Noninvasive

Invasive and noninvasive BCI systems are distinguished by their method of data extraction. Invasive BCI requires implanting foreign materials into the subject's body. Such materials may include large electrode setups or chemical molecules. However, in order for invasive research to be safe enough for humans, it must first require animal research. It is to no surprise why invasive BCI methods are shied from, due to social pressures to stop funding of such research. Invasive BCIs operate by monitoring single-neuron activity within the subject's brain [8]. While such systems have an improved spatial resolution and might deliver control signals with numerous degrees of freedom, BCIs that depend on electrodes within the subject's cortex face considerable difficulties in attaining and sustaining unwavering long-term recordings. However, due to encapsulation, it is likely that the signals within the invading electrodes will eventually degrade [9]. In addition, small changes in the locations of the electrodes can move the recording sites away from areas that are easily recorded. These issues are crucial obstacles that currently prohibit their clinical use in humans.

Invasive BCI can also be performed through electro-corticography (ECoG), also known as intracranial EEG (IEEG), which is the practice of placing electrodes directly on the brain to record electrical activity. Due to the low signal-to-noise ratio of EEG signals, ECoG is usually an alternative method to extracting data from brain activity. Electrical signals must also be conducted through the subject's skull when using EEG, and since bone has a low electrical conductivity, ECoG would contain a much higher spatial resolution. In addition, ECoG is expected to be safer and have a greater stability in the long-term, compared to the mentioned approach above. This is due to the subdural electrode arrays that are used to record ECOG, which takes away the need for electrode that penetrate into the cortex [9].

On the other hand, non-invasive procedures do not require any kind of implantation and the subject gets to interface with the machine through wearable devices. Most non-invasive BCI systems use electroencephalogram (EEG) signals; i.e., the electrical brain activity recorded from electrodes placed on the scalp. Non-invasive BCI is comparably, more convenient, safe, and inexpensive. However, as mentioned before, this method results in low spatial resolutions. In addition, artifacts such as electromyographic (EMG) signals may obscure readings, and non-invasive BCI systems usually require extensive training for users [10].

To further classify BCI systems, non-invasive BCIs can be classified as "evoked" or "spontaneous". An evoked BCI depends heavily on evoked potentials, which reflects the immediate automatic responses of the brain to some external stimuli. In principle, it is easy to detect evoked potentials through scalp electrodes. The P300 and steady-state visual potential (SSVEP) are the most commonly explored in BCI research. In addition, Slow Cortical Potentials (SCP) are also sometimes used in evoked BCI systems. The necessity of external stimulation does, however, restrict the applicability of evoked potentials to a limited range of tasks.

In contrast, spontaneous BCI systems allow the user to carry out cognitive processes freely [11] because it eliminates the need for external stimulation. This allows for the user to interact with the system in a more natural manner through intent. Such a method is especially beneficial when controlling robotic devices. Some signals spontaneous BCI may depend on are event related de/synchronization (ERD/ERS) and Steady State Evoked Potentials (SSEP).

Exogenous vs. Endogenous

A BCI system is classified as exogenous or endogenous depending on the nature of the recorded signal. Exogenous BCI systems depend on neuron activity evoked by external stimuli. Such stimuli include VEPs or auditory evoked potentials. Exogenous BCI systems do not require intensive training since it is easy to setup their control signals (SSVEPs and P300) [12]. In addition, the signal controls can be detected with a single EEG channel, capable of an information rate of up to 60 bits/min [12].

In contrast, endogenous systems do not rely on an external stimulus; it is based mainly on brain rhythms and other potentials. The users have to learn the skill of producing specific patterns, which will be decoded by the system. Training the users using neurofeedback usually does this. The length of the training varies by subject as well as the experimental strategy and training environment. The strategy chosen for the experiment determines how the user learns and what they must do to produce the required brain activity patterns. Graimann *et al* describes two approaches for endogenous systems: Operant conditioning and performance of specific mental tasks [12].

BCI systems that use the operant conditioning strategy train using feedback. The user must rely on the feedback to learn to produce the intended brain activity. This is a similar strategy proposed in calibration- free robotics [13]. In contrast, motor imagery is the most common mental task used to produce brain patterns that can be reliably produced and distinguished. Motor imagery is activated through the imagination of movements of limbs. The users are to perform such mental tasks without physically executing the corresponding movement. Doing so produces de-synchronization (ERD) and event-related synchronization (ERS) [11].

3 BCI Development

In this section we look first at the typical development framework for BCIs, then briefly survey modern BCI systems. Related issues and limitations are also examined.

3.1 Development Framework

At initial stages of development, all BCI systems follow a similar framework, as shown in Figure 2.

First, the user is either monitored for specific mental states or brain activity, or the user intentionally executes a mental task by modifying his/her brain state [14]. Raw brain signals resulting from the execution or monitoring are then acquired, which get preprocessed in the preprocessing stage. Here, the effects of artifacts and noise will be reduced to improve the signal-to-noise-ratio. Features from the reprocessed data are then extracted, informing the system on what it is supposed to detect. These features become translated into labels with logical meaning, which become inputs to the control interface. These inputs become semantic controls for the application or device, which will provide feedback, shown through the output. The feedback gets delivered back to the user, and the cycle restarts.

3.2 Modern BCI Systems

Modern BCI systems fall into five groups: VEPs, slow cortical potentials; P300 evoked potentials; mu and beta rhythms (sensorimotor rhythms); and neuronal action potentials [4]. They are distinguished as such based on the type of brain signals they use. Slow cortical potential interfaces rely on VEPs, which classify them to be dependent BCIs. On the other hand, the other four groups are classified to be independent BCIs. The following section discusses systems that have been developed using these five groups.

Visual evoked potentials

VEPs refer to electrical potentials that are evoked by brief visual stimuli. These potentials are recorded from the visual cortex and its waveforms are extracted from the EEG. VEPs are mainly used to measure the visual pathways from the eye to the brain's visual cortex. In 2000, Middendorf et al presented a method for using VEPs to determine the direction of the user's gaze [15].

The user faces a screen displaying several virtual buttons that flashed at different rates. Once the user directs his/her gaze at a button, the system determines the frequency of the photic driving response over the user's visual cortex. When the frequency matches that of a displayed button, the system concludes that the user wishes to select it.

Slow cortical potentials

Slow cortical potentials (SCPs) are slow voltage shifts within an EEG that can last from one to several seconds. SCP's correspond to the changes in the level of cortical activity. Positive SCPs are related to the decreased activity in neurons, whereas negative SCPs are associated with neuronal activity [16]. These signals can be self- regulated by any type of user to control external devices through BCI. Shifts in SCP can be used to move a cursor and select targets presented on a computer screen. People can be trained to generate these shits using a thought-translation device. This device shows visual-auditory marks so that the user can learn how to shift the SCP levels [17].

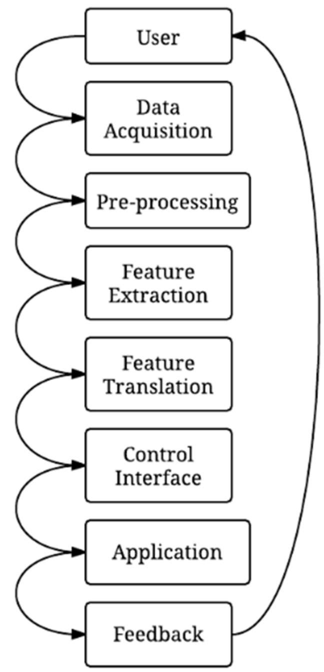

Figure 2: Generic model of BCI development cycle

P300 evoked potentials

P300 evoked potentials are the peaks found in an EEG due to infrequent visual, auditory, or somatosensory stimuli. The use of P300-based BCI systems does not require any training. However, its performance may be reduced since the user eventually adapts to the infrequent stimulus, causing the P300 amplitude to decrease [18]. Typical applications of P300-based BCI systems comprise of matrix of symbols in which selection of such symbols depends on the user's gaze.

Mu and beta rhythms

Mu and beta rhythms combine to create sensorimotor rhythms, which are oscillations in the brain activity localized in the mu and beta bands respectively. Sensorimotor rhythms are associated with motor imagery without any movement [19].

This makes sensorimotor rhythms possible for designing endogenous BCIs. Extensive user training is vital because people tend to struggle with motor imagery. Imagining visual images of the corresponding real movements is insufficient for a BCI system. This is because sensorimotor rhythm patterns are dissimilar to motor imagery. Therefore, training should emphasize kinesthetic experiences rather than visual representations of the movements.

One well-known system, presented by Graz, uses sensorimotor rhythms as control signals [20]. The Graz BCI system is based on ERD and ERS of sensorimotor rhythms. The user participates in an initial session to select a motor imagery paradigm. In each series of timed trials, the user imagines an action while EEG is submitted for feature extraction. After interpreting the user's motor imagery into an output, it is presented back to the user in the form of online feedback. In contrast, with the Wadsworth BCI system, people learned to control a cursor in one or two dimensions to target on a computer screen [21]. During the initial sessions, most users employ motor imagery to control the cursor. However, as they continued to train, imagery becomes less important and users moved the cursor from pure muscle memory.

Neuronal action potentials

In BCIs that rely on action potentials, cone electrodes are inserted into the motor cortex to detect the single cortical neuron-induced potentials [3]. So far, only one user has been able to control neuronal firing rates and uses this ability to move a cursor to select items on a computer screen. Although recurring illness and medication effects limited training, the results have been encouraging. By demonstrating this control in people who are nearly completely paralyzed, this initial data propose that cortical neurons can support an independent system [4].

3.3 Issues and Limitations

Several issues obscure the further development and widespread application of brainwave technology. The first issue is the information transfer rate. The maximum information rates of current BCI devices are offered at 5-25 bits/min [22]. Increasing this rate would be potentially useful in developing applications where the users need to interact with their environment in a timely fashion. Another issue lies in the training time for users to familiar themselves with the system. In spontaneous BCI systems, user training is unnecessary, but evoked BCIs often require extensive training. However, one of the main challenges of a spontaneous BCI system is the non-stationary nature of the EEG signals, which is apparent in the differences between the training and test data sets [13]. In addition, changes in the user's brain processes (e.g., due to distractions, fatigue, etc.) during online operation may affect the system's performance as well.

Intuitively, the less invasive the technique, the more likely it can be used in a wide range of applications. Implanted electrodes provide stability of location, freedom from artifacts, and much higher signal-to-noise ratio (SNR). But one difficulty in such a system is how to determine the locations and the number of the electrodes. Another difficulty is how to keep the system stable over long periods.

4 BCI Applications

Robotics

Within the last ten years, researchers were able to successfully perform invasive procedures that allowed primates to control machines with their brains. Carmena *et al* demonstrated a primate's to learn to control a robot arm through brain-machine interfaces [23]. In addition, Serruya *et al* suggested that neural based control of movement might be suitable for humans through multi-electrode array implant [24]. This theory was based on a monkey's success in moving a computer cursor to any new position in its workspace.

For humans, non-invasive methods based on EEG signals are preferable because of ethical concerns and medical risks. Despite their poor signal-to-noise ratio, recent experiments have shown for the first time that EEG is sufficient for humans to continuously control a mobile robot similar to a wheelchair. In Galán *et al's* paper, experimental results have shown that subjects can quickly master their EEG-based BCI to control a wheelchair [25]. They can also autonomously operate the BCI over a long period of time, which demonstrated it's the system's ability to allow continuous mental control for the user.

In a paper written by Millán *et al*, two human subjects learned to drive the robot between rooms in a house-like environment by mental control only [26]. Furthermore, mental control was only marginally worse than manual control on the same task. It was also shown that a device was able to operate through BCI-based control without any calibrations prior [13]. This device was able to learn an intelligent behavior solely through feedback received after performing each action.

Entertainment

Recent developed BCI applications have focused on those who do not have any disabilities. One of such applications incorporates BCI with gaming. Researchers at University College Dublin and MediaLabEurope have created a BCI-based virtual reality game, *MindBalance* [27]. The character is balancing on a tightrope, and the goal of this game is to maintain its balance using only EEG.

One of the more popular novel devices in present-day is the cat ears headband, manufactured by the company *NeuroSky*. Popular among cosplayers, these cat ears will move in correspondence with the user's mood. Though not very useful, this headband is used mainly as an accessory to a costume.

5 Discussion

We believe that non-invasive BCI systems will become more predominant due to ethical and safety reasons. Unfortunately, the frustrations that arise due to the non-invasive approach will continue to remain and hinder a rapid progression in the field, as discussed in Section 4. However, this is not to say that BCI research for fully capable and robust systems will eventually reach a dead end. Some issues may be resolved if BCI systems were not so heavily dependent on specific brain signals. So far, existing BCI systems rely on methods that require intensive user calibration. This opens up many opportunities for false detection within input brain signals.

We have shown that BCI can play a significant role in AI research due to the varied and promising potential it possesses. Judging from its integration with AI up until now, we can expect a BCI research to continue in this direction. Within the last ten years, the progress of BCI development was revealed through its integration with robotics. It was shown that a device was able to operate through BCI-based control without any prior calibrations [13]. This device was able to learn an intelligent behavior solely through feedback received after performing each action. As shown by the paper by Millán *et al*, two human subjects learned to drive the robot between rooms in a house-like environment by mental control only [26]. These examples demonstrate how easily the two fields complement each other.

To further exploit the potentials of BCI, machine learning methods can be applied to BCIs as well [28]. A successful BCI system, capable to learn, possesses the ability to classify various features obtained from the user's brain activity and performs an action as a result. Classification, essentially, is what allows for the 'mind control magic' to occur in BCIs. Unfortunately, classification methods in general still have not been perfected. Furthermore, classification becomes difficult in BCIs because one must distinguish brain activity intended for control from other types of activity.

6 Conclusion

In this paper we have provided a general overview of research and development for BCI systems. The paper focused on the software end of BCIs, providing a general sense of the various ways one can approach BCI development. The three categories of BCIs were discussed, in addition to their relationships to modern BCI systems. Issues and limitations that BCI development currently faces as well as several existing applications developed were also presented. Furthermore, possible improvements and directions of future work were briefly discussed.

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Disclaimer

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