Brain Controlled Games: Concepts and Classifiers

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Abstract. This paper reviews the concepts behind a brain-computer interface and some of the machine learning methods used to classify a signal coming from an electroencephalogram for brain-controlled game use. After several decades of research, development and application in the rehabilitation domain, modern brain computer interface techniques show a relative maturity, receiving more attention in real world applications, also for the general population, and in particular in the domain of NeuroGames. These are games that use the latest emotional, cognitive, sensory and behavioural techniques to create radically compelling experiences to engage and entertain gamers.

1 INTRODUCTION

Human-computer interaction has become ubiquitous and the traditional keyboard and mouse approach has been replaced by more natural touch and gesture interfaces as a main stream interaction modality. Furthermore there is a need to develop even more natural or involving interaction methods that can also be used in situations where other types of interface are not viable (e.g. disability) or where the experience needs to be enhanced beyond what other interaction methods can offer. Brain-computer interfaces (BCI) provide an alternative communication path based on the brain's neural activity, that is independent from the normal output pathways of peripheral nerves and muscles [1].

The traditional application for BCI mainly focuses on improving the personal assistance and interaction experience for disabled people. Modern BCI techniques are receiving more and more attention in real world applications,- particularly in the domain of BCI applications, such as NeuroGames [2]. NeuroGames include brain-controlled games, also called Neurofeedback games or brain-computer interfacing games, but also augmented reality experiences, cognitive enhancing devices, neuromodulation systems, eye tracking, voice activation, and many more techniques that can improve gamers' immersion. A review of some Brain-Controlled Games is given in section 4, while section 2 and 3 review BCI concepts and classifiers. [1]

2 BCI AND ELECTROENCEPHALOGRAM

A brain–computer interface is based on the idea that we can record the electrical activity in the brain by means of the electroencephalogram (EEG) and use it to interact with a computer program.

EEG is defined traditionally as the electrical activity of the brain recorded from the scalp [3]. It also referred to as the continuous measurement of electrical potential differences between points on the scalp. These electrical differences or activity is the result from ionic current flow within the brain's neurons and some extent glial cells. The measured voltage is in µV (microvolt) and typically recorded at multiple sites on the scalp simultaneously [4].

The scalp EEG considered an important diagnostic and research tool for many reasons as it allows researchers to:

- Monitor the activity of neurons in time of milliseconds, with its high temporal resolution
- Utilise a non-invasive method
- Record using an inexpensive and simple method
- Monitor brain activity in a freely moving subject

EEG signals vary from low to high frequencies, in which there is a general consensus to divide the frequency range within which EEG signals can occur into a number of frequency bands that have been named after Greek letters[3]:

- Delta= 1.0 - 3.5 Hz
- Theta= 4.0 – 7.5 Hz
- Alpha= 8.0 – 13.0 Hz
- Beta= 14.0 – 30.0 Hz
- Gamma= 30.0 – 100.0 Hz

However, despite EEG's limitations of suffering from high susceptibility to noise and poor spatial resolution, it has been widely used to study the brain dynamics as it is effective in detecting immediate responses to stimuli with a good temporal resolution. EEG based BCI systems have been developed to be more practical by being mobile and cost-effective with less physical restrictions. For these reasons, EEG has been considered as a primary option for developing BCI systems[5].

2.2. The BCI approach

In brain-controlled games, or games driven by a brain-computer interface, in order to exercise control, the user voluntarily or involuntarily produces different brain activity patterns that are identified by the computer system and translated into commands. This is usually performed via signal processing and classification algorithms. In figure 1 a simplified model of a BCI system is described.

In particular the brain signal is collected via and EEG and artefacts are eliminated. Artefacts are errors introduced into the signal due to both patient-related issues (e.g. minor body movements, eye movements, sweating) and technical issues (e.g. Hz, impedance fluctuation, cable movements, broken wire contact, too much gel or too little, low battery).

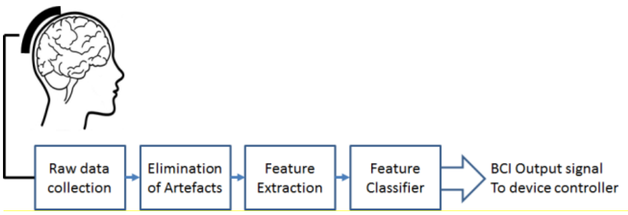

Figure 1 – Simplified functional model of a BCI System

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Artefacts can be eliminated automatically or manually. For example, artefacts can be eliminated automatically by utilizing other sensors and electrodes to monitor and remove them. An example of manual artefact elimination could involve video recording the user during the experiment and reviewing the signal at times in which movements have occurred. Once the artefacts are eliminated, feature extraction is performed. This is needed in order to transform the input signal into a set of features (variables) which are identified as the most relevant information for representing the signal, whilst reducing its size. Feature extraction algorithms can use various techniques; for example, the probabilistic procedure used in Principal Component Analysis, which uses the orthogonal transformations to covert a set of observations of possibly correlated variable into a set of uncorrelated variables (the principal components). Programs like MATLAB, or EEGLab, which is a toolbox for data processing dedicated to the analysis and visualization of continuous data, can be used for such task.

After the feature extraction, and before the signal can be used as the controller for the game, feature classification needs to take place.

3 CLASSIFIERS USED IN BCI:

Lotte et al. in 2007 [6] provide a review of ~~the~~ commonly employed signal classification algorithms together with a review of their critical properties, and guidelines on how to choose the right classifier for the given context of use of the BCI. Here we provide a short review also including research beyond 2007.

Classifiers used to categorise the brain signals can be divided into four different categories: a) linear classifiers, b) neural networks, c) nonlinear Bayesian classifiers and d) nearest neighbour classifiers, as shown in Figure 1. This section will discuss briefly the popular classifiers and their most important properties for BCI applications [6]. These are shown in table 1 and reviewed in the sections below.

3.1. Linear classifiers

Linear classifiers are probably the most popular algorithms for BCI applications. Two kinds of linear classifier have been used for BCI design, Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM).

LDA, or Fisher's LDA, has a very low computational requirement that makes it suitable for online BCI system. Moreover this classifier is simple to use and generally provides good results. Consequently, LDA has been used with success in a great number of BCI systems such as motor imagery based BCI like P300 speller which is a spelling device with a 300ms delay that utilises the P300 visual response signal. The main drawback of LDA is its linearity; this can provide poor results on complex nonlinear EEG data. A Regularized Fisher's LDA (RFLDA) has also been used in the field of BCI; this regularized version of LDA may give better results for BCI than the non-regularized version according to Muller et al. 2004 [7]. Surprisingly, RFLDA is much less used than LDA for BCI applications.

Support Vector Machine (SVM) classifier has been applied with success to a relatively large number of BCI problems but this success is gained at the expense of a low speed of execution [8] .

3.2. Neural networks

Neural networks (NN) along with linear classifiers are the classifiers that mostly used in BCI research. The most widely neural network used for BCI is the Multilayer Perceptron (MLP) and briefly present other neural network classifiers used for BCI applications. Below are described two of the most used classifiers.

MLP has been applied to almost all BCI problems, due to the fact that it can classify any number of classes, giving this classifier the flexibility to adapt to a variety of problems. A Multilayer Perceptron without hidden layers is known as a Perceptron. A perceptron is equivalent to LDA and, as such, has occasionally been used for BCI applications.

According to Millan et al. [9] a Gaussian classifier, outperforms MLPs on BCI data, and can perform efficient rejection of uncertain samples. Consequently, this classifier has been applied with success to motor controlled classification experiments.

Other NN methods mentioned by Lotte et al. [6] that can be used in BCI are:

• Learning Vector Quantization (LVQ) Neural Network
• Fuzzy ARTMAP Neural Network
• Dynamic Neural Networks such as the Finite Impulse Response Neural Network (FIRNN), Time-Delay Neural Network (TDNN) or Gamma dynamic Neural Network.
• RBF Neural Network
• Bayesian Logistic Regression Neural Network (BLRNN)
• Adaptive Logic Network (ALN)
• Probability estimating Guarded Neural Classifier (PeGNC).

3.3. Nonlinear Bayesian classifiers

This section introduces two Bayesian classifiers used for BCI: Bayes quadratic and the Hidden Markov Model (HMM). Although Bayesian Graphical Network (BGN) classifiers have been employed for BCI, BGN is not described here as it is not common, and is not currently fast enough for real-time BCI and games. However, these classifiers are not as widespread as linear classifiers or Neural Networks in BCI applications.

Bayes quadratic classifier is not widely used for BCI, but it has been applied with success to motor controlled classification [6].

Hidden Markov Models (HMM) are popular dynamic classifiers used in the field of speech recognition, and are perfectly suitable algorithms for the classification of time series. As EEG components used to drive BCI have specific time courses, HMM have been applied to the classification of temporal sequences of BCI features and even to the classification of raw EEG. HMM are not widespread within the BCI community.

Another kind of HMM which has been used to design BCI is the Input-Output HMM (IOHMM). The main advantage of this classifier is that one IOHMM can discriminate between several classes, whereas one HMM per class is needed to achieve the same operation.

3.4. Nearest Neighbour classifiers

This section will cover two types of classifiers, the K Nearest Neighbours (KNN) and Mahalanobis distance.

KNN algorithms are not very popular in the BCI literature, probably because they are known to be very sensitive to the dimensionality of the EEG signal, and they have failed in several BCI experiments [8][7][10]. However, when used in BCI systems with low-dimensional feature vectors, KNN prove to be efficient [11].

Mahalanobis distance is simple yet robust classifier which has proved to be suitable for BCI systems [10][12]. Despite its good performances, it is still scarcely used in the BCI literature.

Table 1 – Classifiers used in BCI research [6]

Linear Classifiers	Linear Discriminant Analysis (LDA)	Fisher's LDA (FLDA)
		Regularized Fisher's LDA (RFLDA)
	Support Vector Machine (SVM)	Gaussian SVM
		Radial Basis Function SVM (RBF SVM)
Neural Network (NN)	Multilayer Perceptron (MLP)	
	Gaussian NN	
	Learning Vector Quantization (LVQ NN)	
	Fuzzy ARTMAP NN	
	Dynamic NN	Finite Impulse Response (FIRNN)
		Time-Delay NN (TDNN)
		Gamma Dynamic (GDNN)
	RBF NN	
	Bayesian Logistic Regression NN (BLRNN)	
	Adaptive Logic Network (ALN NN)	
	Probability estimating Guarded Neural Classifier (PeGNC)	
	Perceptron	
Nonlinear Bayesian Classifiers	Bayes Quadratic	
	Hidden Markov-Model (HMM)	HMM
		Input-output (IOHMM)
	Bayesian Graphical Network (BGN)	
Nearest Neighbour Classifier	K Nearest Neighbour (KNN)	
	Mahalanobis Distance	

4. BCI GAMES

Several Brain Controlled Games have been developed though out the years. Bos at al. [13] provided a review of the state of the art of the use of BCI in games in 2010. Here we report them considering a different point of view, which is how the signal is used in the game, or paradigm. Additionally, some of the games that have been missed as well as some methodological advancement from 2010 onwards are reviewed and summarised in table 2.

One of the first brain-controlled games was created by Vidal (1977) [14]. In the game, the user can move around the maze in four directions by focusing one's eyes or attention on one of four fixation points displayed off-screen. A diamond-shaped checkerboard is periodically flashed between the four points that will result in neural activity on different sites of the primary visual cortex. This visually evoked potential (VEP) is recognized using an online classification method to move in the maze. The game performance was remarkable despite being the first game of its kind. The use of online artefact rejection and adaptive classification made Vidal's approach way ahead of its time. One factor to note is the fact that Vidal's game used eye movements, which are considered artefacts capable of interfering with the original EEG signal [15].

A simpler method to integrate brain signals into a game is the interpretation of broadband frequency power of the brain such as alpha, beta, gamma and mu-rhythms. This method is used in the game called "Brainball" by Hjelm (2000) [16], where the EEGs of the two players is measured using a headband. A relaxation score is derived from the ratio between the alpha and beta activity in the EEG signal. The relaxation score is used to move a steel ball across the table and away from the most relaxed player; However, when the ball is almost at the opponent's side, and the player realizes s/he is about to win, if excitement sets in, the player might lose instead [15]. Another BCI game by Van der Laar et al. (2013) [17] is called "World of Warcraft" (WoW) and it uses the power in the alpha band over parietal regions. This is a massive multiplayer online role-playing game where the objective is to level up and get a better abilities and weapons by achieving experience points through completing quests, slaying enemies and exploring the world. In the BCI version of the game, the user (character in the game) can change from one form to another by switching between a state of relaxation and alertness (increase of alpha band activity). The shape of the Night Elf in the druid shape who is strongly dependent on intelligence and mental concentration has been mapped to the state of relaxed alertness. The decrease in the alpha band activity, such as in a state of stress or agitation, provides a natural mapping to the bear shape, a figure eager to fight. Users can train in the use of their alpha levels very quickly. The authors report that a subject has learned to control alpha levels to such an extent that intentionally transforming every 5 seconds was possible.

Another interaction method that makes use of the BCI techniques is as neuro-feedback. This is used for example in the experiment of Pope and Palsson (2003) where children with attention deficit hyperactive disorder (ADHD) were treated using neuro-feedback. One group used standard neuro-feedback, while another group played Sony PlayStation™ video games where the controller input was modulated by a neuro-feedback system developed by NASA. In the latter the correct brainwave patterns were rewarded with a more responsive controller. Mastering control over brain signals is often the goal of the game in this sort of applications, where the characteristic of a neuro-feedback game is that the player has to discover how to control aspects of brain activity to play the game competently [15], where it is hope that such learning can be transferred to the real world.

In contrast to the previous methods, motor-control based BCIs are considered as a traditional input device for BCI games. One example is a game by Pineda et al in 2003 [18], where they used the mu-rhythm power of the motor cortices to steer a first person 3D shooter game, while movement forward/backward was controlled using physical buttons. No machine learning was involved. The players learned to control their mu-power by training for 10 hours over the course of five weeks. Another motor-control BCI game is "Pacman" by Krepki et al. (2007) [19], in which the detection of movement is based on the lateralised readiness potential (LRP). This is a slow negative shift in the electroencephalogram (EEG) signal that develops over the activated motor cortex starting sometime before the actual movement onset. In the BCI game, Pacman makes one step every 1.5–2 seconds, and moves straight until it receives a turn command or reaches a wall. Users sometimes reported the feeling that Pacman moves in the correct direction even before the user was consciously aware of that decision, this is an example of a new level of interaction mechanism that happens so naturally that is unconscious, such natural level of interaction can only be enabled within a BCI game [15].

Table 2 – BCI controlled games

Author	Game name	Original Game author	BCI method
Vidal (1977)	-	Vidal	Evoked Potentials (VEP)
Hjelm (2000)	Brainball	Hjelm	Neurofeedback (alpha and beta)
Laar et al. (2013)	World of Warcraft	Blizzard Entertainment	Neurofeedback (alpha band power)
Pope and Palsson (2003)	-	Sony	Neurofeedback
Pineda et al in 2003	3-D first-person shooter game	-	Motor-control (mu-rhythm power)
Krepki et al. (2007)	Brain Pacman	Krepki et al.	Motor-control (LRP)
Bayliss et al.(2003, 2004)	Virtual reality scene	Bayliss et al.	Evoked Potentials (P300)
Lalor et al. (2004, 2005)	theMindBalance	Lalor et al.	Evoked Potentials (SSVEP)
Martinez et al. (2007)	2D racing game	Martinez et al.	Evoked Potentials (SSVEP)
Jackson et al. (2009)	Shooter game	-	Evoked Potentials (SSVEP)
Mühl et al. (2010)	Bacteria Hunt	Mühl et al.	Evoked Potentials (SSVEP)
Tangermann et al. (2009)	Pinball	-	Motor control

Evoked responses refers to a paradigm where the application measures the response to a stimulus. This is very different method from the neuro-feedback and the motor-controlled BCI games, where the user can initiate actions without depending on stimuli from the game. An example of an evoked response is the P300, an event related potential (ERP) that occurs after a task-relevant stimulus is presented. Bayliss uses a P300 BCI in a virtual driving task and a virtual apartment (2003, 2004) [20][21]. Objects in the virtual apartment were highlighted using a red translucent sphere, evoking a P300 when the object that the user wanted to select was highlighted [15]. A lower-level evoked paradigm is based on steady-state visually evoked potentials (SSVEPs), in which the attention to a visual stimulus with a certain frequency in the visual cortex is measured as a modulation of the same frequency in same area. In a game called “theMindBalance” by Lalor et al. (2004, 2005) [22][23], a SSVEP is evoked by two different checkerboards. The attention focused on one of the checkerboards is used to balance an avatar on a cord in a complex 3D environment.

One advantage of the evoked responses over induced BCI paradigms is that it allows easy selection of one out of multiple options by focussing attention on a stimulus. For example, a 2D racing game by Martinez et al. (2007) [24] uses four different directional controls using SSVEP, and in a similar way a shooter was controlled in Jackson et al. (2009) [25]. These games could be improved by using evoked potentials to measure the mental state of the user, and use it as new information source as opposed to a button press. By assigning a meaning to the mental action of concentrating on a game element, for example devouring a bacteria as in the “Bacteria Hunt” game by Mühl et al. (2010) [26], the user reports the feeling of becoming part of the game mechanics, and promotes a more involving and enjoyable interactions. The same applies for games that use imagined movement. These games replace the movement of interaction with buttons with a (slow) imagined movement, without adding the role of precise timing between thinking about the movement and the actual movement on the screen as shown in a “Pinball” experiment by Tangermann et al. (2009) [15][27] where the user can utilize the extracted and classified band power features to control the left and the right pedals of a Pinball machine.

7 CONCLUSIONS

We have introduced the methods used to create a BCI and presented some of the research conducted to produce Brain Controlled Games that replace the traditional input like keyboard, mouse and joysticks with an interaction mechanism based on brain waves that has the potential to be more involving and enjoyable. The different tools, techniques and paradigms used to date have been introduced together with the games in which they have been applied. These games have attracted a small population of gamers. The main challenge of the BCI process application to games is the ability to perform all the tasks of signal handling, as highlighted in the modules in fig. 1, in real-time rather than post experience, or as very slow process of voluntary signal production. Methods like Neurofeedback, Motor control and Evoked responses have been utilized in different BIC controlled games. The paradigm used in the game can be used both for interacting with the game, but also to evoke responses congruent with the experience, supporting immersive and natural interactions with the game world. This would be particularly usefully in area in serious games. Further research is needed in order to provide a fully involving game experience, and thus replace the traditional interaction methods.

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