A Game-based Learning Framework for Controlling Brain-Actuated Wheelchairs

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KEYWORDS

Brain-computer interface, electroencephalography, virtual reality, low-cost commercial-off-the-shelf products.

ABSTRACT

Paraplegia is a disability caused by impairment in motor or sensory functions of the lower limbs. Most paraplegic subjects use mechanical wheelchairs for their movement, however, patients with reduced upper limb functionality may benefit from the use of motorised, electric wheelchairs. Depending on the patient, learning how to control these wheelchairs can be hard (if at all possible), time-consuming, demotivating, and to some extent dangerous. This paper proposes a game-based learning framework for training these patients in a safe, virtual environment. Specifically, the framework utilises the Emotiv EPOC EEG headset to enable brain wave control of a virtual electric wheelchair in a realistic virtual world game environment created with the Unity 3D game engine.

INTRODUCTION

The ability to move around, explore our surroundings and being able to transfer to other places in order to take part in daily activities is an essential quality in human life. People with disabilities may lack this ability due to their illness. With the aid of prostheses or wheelchairs, many disabled people can be become more mobile. However, it may be very difficult or even impossible for tetraplegic patients, or paraplegic patients with reduced upper limb functionality, to control an electric wheelchair via a joystick or other manual control devices. For these patients, an electric wheelchair that can be operated solely by the mind could provide a formidable improvement in the quality of life.

Prior to the development of brain-actuated wheelchair, several factors must first be considered. In order to map out the needs and shortcomings of the available technology it is desirable to test the existing technology in a virtual environment. This enables the exploration, testing and development of the user interface and brain-computer interface (BCI) functionality.

This paper presents the development of an open-source framework for disabled people such as tetraplegics or sufferers of amyotrophic lateral sclerosis (ALS) to control a brain-actuated wheelchair in a virtual environment. The framework is realised by exclusively adopting low-cost commercial off-the-shelf (COTS) components and tools. In particular, an electroencephalography (EEG) headset, the Emotiv EPOC, is chosen for monitoring the subject's brain waves. These signals are then used as inputs for controlling a wheelchair in a simulated environment. To achieve this goal, the Unity 3D game engine is selected as an efficient integration platform. The adopted design choices make the proposed framework very flexible and extremely low-cost.

In the following sections, we first provide a background of game-based learning, EEG technology, related work, and our motivation and aim. We proceed with describing our game-based methodology before presenting the framework architecture, including the Emotiv headset and library and the Unity environment, the interface between the headset and Unity, design of the game environment, and a preliminary artificial neural network (ANN) (Yegnanarayana, 2009) for converting raw EEG brain waves into control signals. Finally, we present the results of our work and a discussion, including future work.

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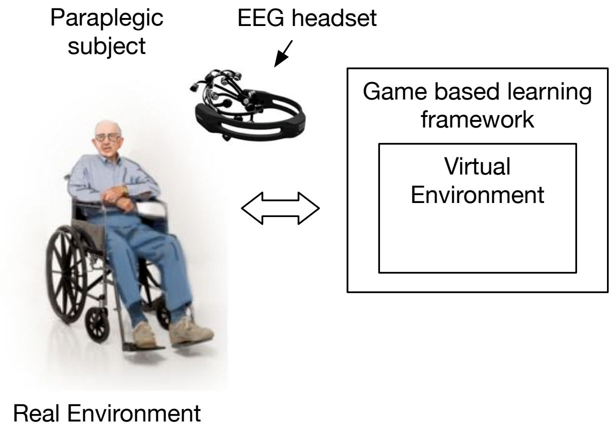

Figure 1: Game-based learning framework for paraplegic subjects to control brain-actuated wheelchairs.

BACKGROUND

There is a rapidly growing body of empirical evidence on the effectiveness of using video and computer games to provide instruction (Tobias et al., 2014). We experience pleasure when actively engaged in games, especially in coming to understand how a new system works. This is true whether the game is considered “entertainment” or “serious” (Susi et al., 2007). Here, we adopt a game-based learning approach, where a ”serious” game is developed to engage disabled subjects in learning how to control their wheelchair by using brain waves. We believe our approach is especially suitable for this kind of training, because mastering brain wave control can be difficult and involve tedious and repetitive tasks and thus be demotivating for the subject. Figure 1 illustrates the main idea and a high level view of the components involved in the game-based learning framework.

EEG Technology

EEG is an electrophysiological monitoring method that measures the natural electric potential on the scalp (Niedermeyer and da Silva, 2005). Physiologically, EEG power reflects the number of neurons that discharge synchronously (Klimesch, 1999). This electric potential is a result of brain activity and behaves in a periodic, wavelike fashion referred to as brain waves and can be recorded with a portable EEG headset such as the Emotiv EPOC EEG (e.g., Duvinage et al., 2013).

Traditionally, EEG technology has been a diagnostic tool for medical professionals in order to diagnose neurological disorders such as epilepsy, brain tumors and more (Vaque, 1999). In recent years, EEG technology has seen a commercialisation which has resulted in affordable EEG equipment for both researchers and end-consumers. One such device is the Emotiv EPOC headset, which comes with several pieces of software developed for BCI. The included software enables the user to both record and investigate their brain wave activity in real time with the brainwave signals split into the conventional EEG frequency bands, namely the delta ($<$ 4 Hz), theta (4–7 Hz), alpha (8–15 Hz), beta (16–31 Hz), and gamma ($>$ 32 Hz) bands, of which the alpha band, which is active during an alert and cognitive state of the patient (Klimesch, 1999), and the beta band, which is closely related to purposive movement (Niedermeyer and da Silva, 2005), are the most important with respect to BCI.

One of the features of this software is the ability to store specific brain wave patterns as commands. Up to four different user-defined commands can be stored (e.g., up, down, left, right), and the proper software for mapping and training these commands are provided. The application programming interface (API) provided by Emotiv enables software developers to access these commands and use them in their software, achieving BCI as a result.

Related Work

The possibility of using EEG technology for medical assistant applications has been studied in the literature. In particular, the possibility of enabling disabled subjects to control their wheelchairs by using brain waves has been investigated by several research groups. For instance, an attempt to use brain signals to control mechanical devices such as wheelchairs was presented by Tanaka et al. (2005). To achieve this goal, a recursive training algorithm to generate recognition patterns from EEG signals was developed. Relevant experimental results demonstrated the potential of the proposed system. In particular, the system was tested in a real experimental scenario where subjects were required to approach target positions by repeating movements. However, this experimental setup required external assistance for the subjects because the wheelchair was supposed to be stopped during EEG detection and pattern matching, since the processing time was very slow. Successively, thanks to different advances in this technology, a real-time EEG classification system was presented by Craig and Nguyen (2007), with the goal of enhancing the control of a head-movement controlled power wheelchair for patients with chronic spinal cord injury (SCI).

One of the main challenges that characterises most of these previous works is that developing and testing brain-actuated wheelchairs in a real-world environment is very difficult because of the extensive training that is required for the paraplegic subjects to safely operate the systems. In this perspective, even though numerous research efforts have been performed to develop brain-actuated wheelchairs, to the best of our knowledge there exists only a few integrated frameworks for effectively training paraplegic or tetraplegic subjects in controlling their wheelchairs. For instance, the possibility of a tetraplegic for using brain waves to control movements of his wheelchair in virtual reality was first studied by (Leeb et al., 2007). In this study, a tetraplegic subject was able to generate bursts of beta oscillations in the EEG by imagination of movements of his paralyzed feet. These beta oscillations were used for self-paced (asynchronous) BCI control based on a single bipolar EEG recording. The subject was placed inside a virtual street populated with avatars. Even though the use of a visual-rich virtual environment was proved to be a very effective approach for improving efficiency of virtual training, the possibility of adding some elements of game-based learning was not deeply considered.

Motivation and Aim

As described above, development and testing of brain-actuated wheelchairs for paraplegic patients in a real-world environment is challenging due to safety concerns. Only recently did researchers attempt to use virtual reality training to overcome this challenge but failed to include the advantage of game-based learning aspects. Moreover, using a virtual environment enables an adaptive and incremental learning paradigm, where training exercises are matched with the level of skill attained by the users. Finally, virtual environments are easy to modify and extend in software compared to their physical counterparts.

Motivated by these factors in an emerging field of research, our aim is to propose a game-based learning framework for brain-actuated wheelchairs, developed in only a few months by a small group of people, and involving only low-cost COTS components, that incorporates many of the advantages a virtual training environment can offer.

METHOD

This section describes the implementation details of our framework, and the rationale for some of our design decisions.

Game-based Methodology

The aim of implementing game-based learning concepts is to create a training environment in such a manner that the trainee is learning while at the same time enjoying the game aspects of the exercises. The skills and knowledge provided by the experience of playing the game can then later be applied in real-life scenarios.

Several aspects of game-based learning have been implemented in our virtual training environment in order to enhance learning, including

- safe risks, where users can experience consequences from their mistakes in a safe environment;
- goal-based tasks, where an on-screen prompt informs the user about the current task;
- incremental learning, where the user is prompted to complete more challenging tasks as the game progresses; and
- timed events, where users can compare themselves with their previous times.

Learning to consistently switch between input commands is imperative to safely operate a brain-actuated wheelchair. In our virtual environment, the user can explore and test the wheelchair functionality in a setting free from risk in order to improve their BCI skills. As a result, a patient utilizing a brain-actuated wheelchair in the future may greatly benefit from the experience gained in the game-based learning environment.

Users can also benefit from competing against themselves, for example trying to reduce their completion time for a particular game level. A shorter completion time would likely be due to better ability to switch input commands.

We have attempted to address some of the advantages of a game-based methodology in our implementation. For example, we have included the abovementioned game completion timer that accompanies an onscreen description of the task at hand where it is relevant. Furthermore, we have created an environment with an emphasis on step-by-step self-paced incremental learning, where users complete game levels with progressively more difficult tasks, exploring different aspects of the skills needed to operate an electric wheelchair in a real-world environment.

The proposed game-based training methodology follows the game levels depicted in Figure 2. In Level 1, users begin by concentrating on only learning and practicing a single input command, namely that of moving forward in a "drag race," in which the task is to drive the wheelchair straight forward from the starting line to the finish line. After this level has been completed, the player can choose to repeat the level in order to improve completion time, or to proceed to more challenging tasks involving several input commands. Specifically, in Level 2, the user will learn to switch between movement commands in order to navigate a labyrinth. In Level 3, users learn to handle safety mechanisms, whereas Level 4 offers more difficult and advanced tasks for improving navigation skills. Finally, Level 5 provides users with a realistic real-world scenario, where users must navigate the wheelchair in an urban area, using all the skills they have learnt previously.

Framework Architecture

The framework consists of two main components: the EEG headset and the game engine. The choice of these two components is crucial for the success of the framework. In this section, each of the main components are explained and finally the interfacing between the game engine and the EEG device is described in detail.

Emotiv Headset and Library: The EEG device connects the user's brain to the virtual environment by converting EEG brain waves measured from one or several electrodes positioned on the user's scalp into BCI commands. There were two factors that we considered the most important when choosing the EEG hardware to achieve our goals, namely convenience and accuracy.

In terms of convenience, the device must be simple for the end user to equip and use. In addition the device should have a good API in order to make it easy for the developer to create software.

In terms of accuracy, it is important that the EEG device provides enough accuracy to differentiate between several mental states for control, e.g. "forward," "left," and "right." This is necessary in order for the user to able to move around freely in an open, unconstrained environment such as the real world.

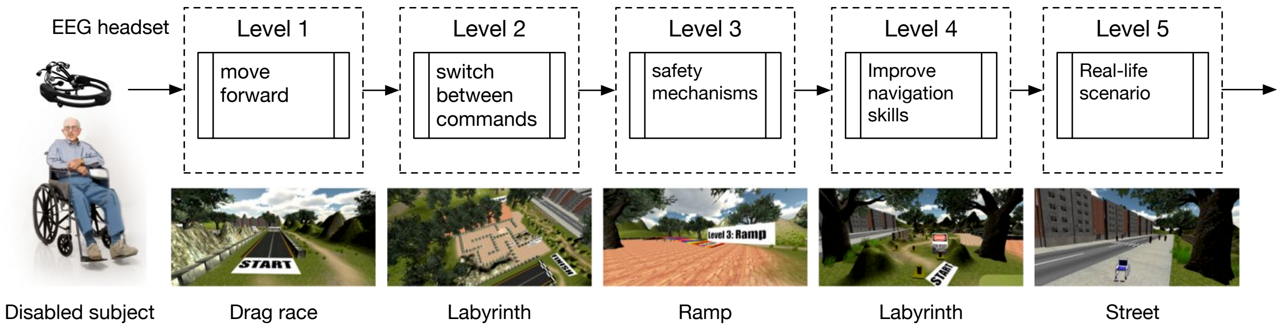

Figure 2: The proposed game-based training methodology. A training sequence of different levels is adopted.

Compared to most conventional medical equipment, the Emotiv EPOC is very convenient to use as it is intended for end-consumers and does not require professional expertise. Considering the nature of how EEG is measured, convenience is not compatible with accuracy and some sacrifices must be made in order to ensure the quality of the measured signals. Nevertheless, compared to other COTS EEG equipment that solely uses dry electrodes, the Emotiv EPOC is designed to be used with a saline solution that is applied to electrodes, thus significantly improving the connection between the capacitive sensors and the scalp compared to dry electrodes.

Furthermore, the numerous electrodes of the Emotiv EPOC along with its advanced software for brain wave pattern recognition enables the device to recognise up to four different mental states that can be used simultaneously for EEG brain control. Whilst the source code of Emotiv software is proprietary and hidden, it is clear that the recognition of these mental states is presumably done by means of some advanced machine learning algorithm such as an ANN and is conveniently available to programmers via the API.

Also convenient is the availability of an official plugin compatible with Unity 4.6 that connects the Emotiv API to Unity. This enables software developers to implement in Unity the features provided by the headset with ease. Hence, considering these facts, the Emotiv EPOC provides a solid middle ground between convenience and accuracy.

Unity Environment: A number of 3D game engines for developing virtual environments exist, with perhaps some of the most popular being Unity, Unreal Engine, CryEngine, and Source 2. While each of these have their own strengths and weaknesses, we wish to highlight that the engine of our choice, Unity, is very quick to learn whilst simultaneously being quite advanced, thus enabling very fast prototyping of virtual game environments. Another strength of the Unity game engine is the cross-platform focus of the engine, which potentially enables portability between platforms such as tablets or smart phones in future development. Finally, as stated above, Emotiv has developed an official Unity plugin which further simplifies the relationship between the headset and the game engine. By having access to a readily available plugin to the Emotiv API, choosing the Unity engine ensures that a minimal amount of time is used to interface the EEG device to the game engine and more time can be used to develop the virtual environment.

An illustration of the framework architecture is shown in Figure 3. The Emotiv "EmoEngine" handles the EEG signals from the headset and interfaces with the Emotiv API, enabling programmers to access both raw and processed EEG signal, thus utilizing BCI functionality. The Unity plugin provides an interface between the Emotiv API and the Unity game engine, which is used for creating the virtual training environment. More details on the components and their interaction are provided in the following sections.

Interfacing Emotiv EPOC with Unity

Before the EPOC headset can be used as a BCI, the user must record at least one mental state associated with a "BCI command." This is done via the bundled Emotiv Control Panel. This software stores the user profiles and their relationship between mental states and BCI commands. When the configuration process begins, the user is prompted for a "neutral" state of mind for a short amount of time in order for the algorithm to have a neutral base where no command is active. After the neutral state is stored, the user may proceed to configure up to four other commands, in our case labelled by the Emotiv software as "push," "pull," "left," and "right." These four commands can later be accessed programmatically from within Unity via the plugin. After the desired BCI commands have been recorded, the user can attempt to activate them again inside the wheelchair framework. Importantly, these commands can be mapped to have different meanings in different setting, e.g., "push" can be used as a "forward" command in one particular setting, or mode, while being used as a "choose" command in another mode.

When the headset measures an EEG state similar to a previously recorded EEG state, the EPOC determines how closely it matches the original recording, and assigns it a number in the interval $[0, 1]$, where 1 means a perfect match. Algorithm 1 shows how this information can be accessed in Unity. This particular piece of code is executed at a rate of 60 times per second, and queries the Emotiv plugin for updated information.

When recording the BCI commands it may be beneficial for the user to mentally associate the commands with physical movements. For example, one may associate "push" with walking, and "left" and "right" with movement of the

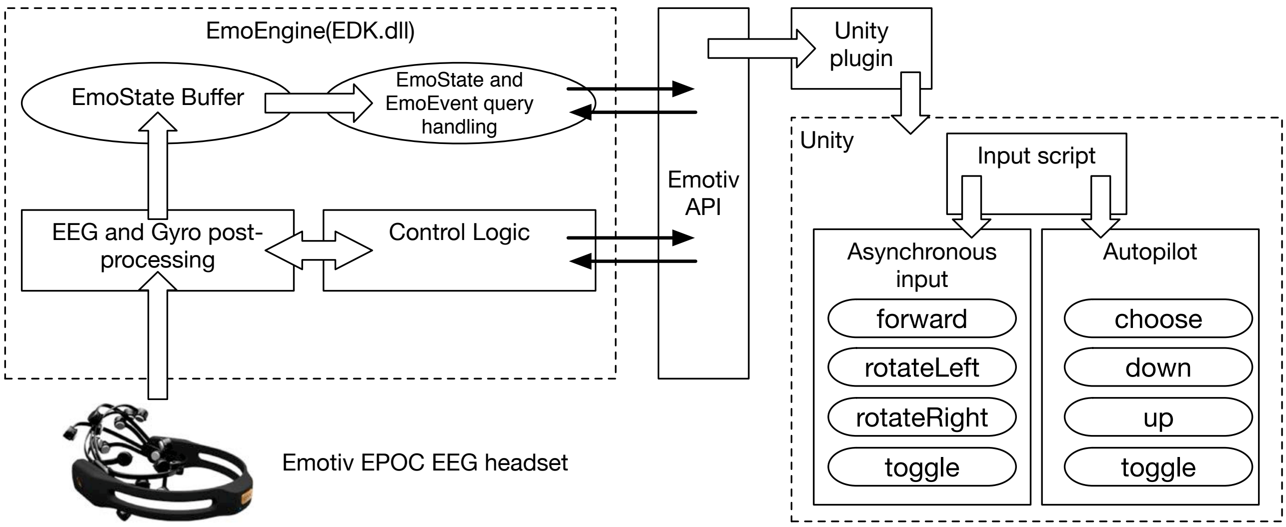

Figure 3: The proposed framework architecture. Some elements of this figure are credit to Emotiv (Emotiv, 2014).

```
void CognitivActionUpdate(){
  int count=0;
  foreach (float f in EmoCognitiv.
      CognitivActionPower) {
    //only the current active command can be
        greater than zero
    if(f>0f) {
      CurrentCognitivPower = f;
      CurrentCognitivAction =
      EmoCognitiv.cognitivActionList[count].
          ToString();
    }
    else count+=1;
  }
}
```

Algorithm 1: Method of obtaining cognitive data from the plugin.

left and right arms, respectively, thus making it easier to reproduce a particular BCI command. However, in cases where the person never had the ability to walk or make arm movements, slightly more creative approaches must be made. For example, some testing was done using various mental images unrelated to bodily movement. An example of this could be to imagine a cube suspended by rubber bands inside one's own head. To imagine the movement or rotation of such a cube will require mental concentration, which in turn affects the EEG state of the user that can be used as a control signal.

Design of Game Environment

This section describes how the environment was created together with the design choices underneath the surface. The aim was to create an open game world where the user can roam freely around the environment whilst having terrain, trees, rubble and buildings limit movement to a reasonable degree. This is done in order to both create an intuitive understanding of what to do and where to go, and at the same time avoid the artificial feeling one might get from a minimalistic design using invisible borders.

The world is divided into five game levels as described previously (see Figure 2), each testing various BCI commands and implemented functions as illustrated in Figure 3.

The wheelchair has two modes of operation that the user can switch between at any time, a manual self-paced asynchronous mode (as opposed to cue-based synchronous mode) and an autopilot mode. We mainly adopt the term "asynchronous" in this paper since this term is commonly used in the literature but for most purposes the term is equivalent to "manual," meaning that the user is not limited by any cues or overridden by an autopilot, but is free to make movements at will.

In the asynchronous mode, the user can move around freely while learning and practicing BCI commands by completing tasks prompted by a context-sensitive graphical user interface (GUI) (an example is shown in Figure 4).

Figure 4: Context-sensitive GUI describing the current objective.

The autopilot mode enables the user to travel between five predefined geographical locations in the virtual environment. The autopilot is realized by utilizing the A*-algorithm (Hart et al., 1968) for pathfinding, and is accessed via the GUI. For real-word purposes, the autopilot would have to incorporate real maps and a means to select target locations, for example by freely available map services online. Great care must also be taken to ensure that the chosen path is safe and accessible for an electric wheelchair.

Being limited to four degrees of freedom impose some challenges when designing how the user should interact with the application, when there are two modes of operation involved. Several designs were considered prior to choosing the design illustrated in Figure 3. The diagram illustrates the inner workings of the Emotiv software engine, and how the virtual environment is connected. The “EmoEngine” receives pre-processed EEG and gyro data from the headset which will then be post-processed into an “EmoState”-structure that contains the currently active BCI command. These structures can be accessed via an “EmoEvent” query which will return the current state. In this case, the querying for an “EmoEvent” is handled by the Emotiv API and the Unity plugin (Emotiv, 2014).

The number of mental commands that the Emotiv software can learn and store for a particular user is limited to four. However, by using modes, we can use these four commands for many different purposes. Specifically, the function activated by a BCI command depends on which mode is currently active, and whether the command’s threshold value has been exceeded.

In asynchronous mode, *forward*, *rotateLeft*, *rotateRight* and *toggle* are activated by the BCI commands “push,” “left,” “right,” and “pull,” respectively. The purpose of the first three commands is to move the wheelchair forward or rotate it to the left or right, whilst the last command is used to switch to autopilot mode and back.

In autopilot mode, the wheelchair is operated in a similar fashion, with the BCI command “push” mapped to *choose*, “left” is mapped to *down*, “right” is mapped to *up*, and “pull” is again mapped to *toggle*. The user uses the *up* and *down* commands to navigate a list of destinations, and then selects it using the *choose* command.

Importantly, when having two or more modes in the game, every mode must include a command for changing modes. Here, we use a *toggle* but for more complex structures, possibly involving many modes and even submodes, a better command could be *back*, which is well know to users of smartphones and tablets.

Preliminary Artificial Neural Network (ANN)

Whilst the Emotiv software for brain wave pattern recognition is a powerful tool for the framework we describe here, it is proprietary and closed source. This may limit the functionality of the framework and also forces it to be compatible with current and future versions of the Emotiv software. We therefore decided to implement a preliminary ANN for EEG pattern recognition and classification. In machine learning and cognitive science, ANNs are a family of models inspired by biological neural networks and are used to estimate or approximate functions that can depend on a large number of inputs and are generally unknown (Yegnanarayana, 2009). This technology is particularly relevant for the application recognising mental BCI commands, with a large number of inputs that need to be considered when acquiring data with an EEG headset.

Here, an experiment was performed to investigate whether an ANN was able to classify two types of EEG states, namely “meditation” and the command “push.“ We collected 200 raw EEG data samples comprised of these two different cognitive states. The first 100 samples were sampled while the user was meditating with closed eyes, trying to become completely relaxed. The other 100 samples were sampled while the user was trying to generate the cognitive action “push,” which can be considered a polar opposite to “meditation.” We used the Neural Network Toolbox in Matlab (Mathworks, Inc., 2015) to implement the ANN and perform the experiment.

During the EEG data collection for the experiment, the user controlled the wheelchair in Unity to ensure that the correct cognitive state was activated, meaning that if the wheelchair was not moving, the “push” sample would be discarded. Measuring the quality of meditation is usually not a straightforward process because the nature of high quality meditation remains subjective. As long as the eyes are closed, less beta activity in the brain can be normally expected. For these reasons and in order to ensure good reliability and accuracy for the considered data set, each data sample was sampled with a duration of 10 seconds by the same user during the same day.

As inputs to the ANN, the mean power spectral density from seven EEG channels was used. The power spectrum was further divided into six frequency bands, namely the delta, theta, and alpha bands, and the low, medium, and high subbands of the beta band. Using some rules-of-thumb and trial-and-error, the number of hidden neurons was set to 21 for best results. Summarising, the ANN therefore consisted of a 6×7 inputs, 21 hidden neurons, and an output categorising the input as either “meditation” or “push“, as depicted in Figure 5. The sample size of the training set was 140, whereas both the validation set and testing set was set to 30 samples.

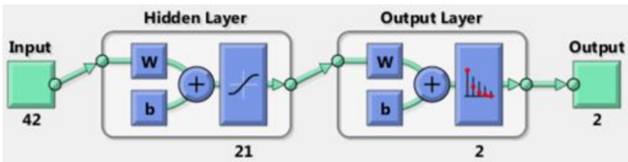

Figure 5: Structure of artificial neural network (ANN) for classification of two EEG states.

Results

A large and realistic urban 3D virtual world has been implemented, in which users can control a virtual brain-actuated wheelchair to navigate this world. Within this virtual environment, there are five incrementally more difficult game levels for game-based learning and practicing of brain control of the wheelchair (see Figures 6–10 for screenshots).

Three young and healthy male students in their twenties using the virtual training environment were all able to learn how to control the virtual wheelchair only with their minds. In particular, the students were able to utilise all

Figure 6: Level 1.

Figure 7: Level 2.

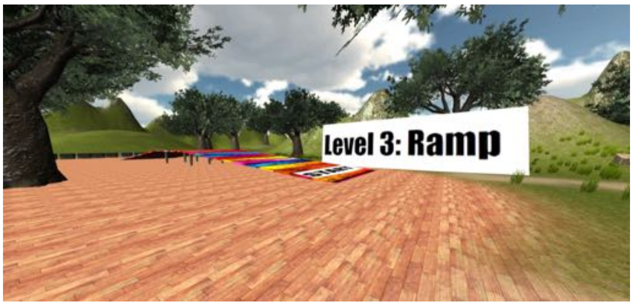

Figure 8: Level 3.

Figure 9: Level 4.


Figure 10: Level 5.

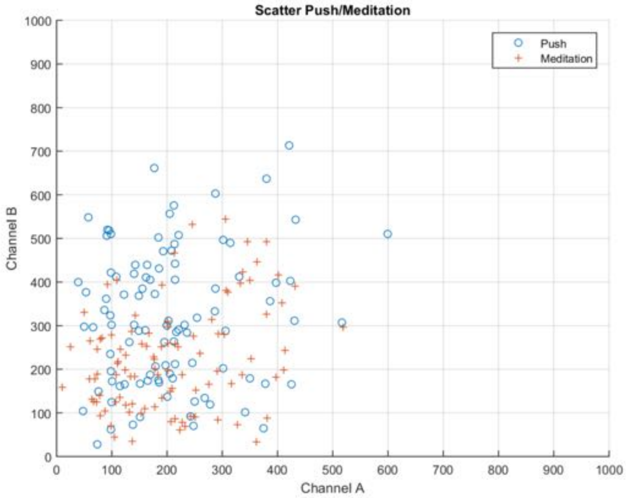

Figure 11: Scatter plot of EEG amplitudes for channel 4 (A) and 7 (B) at 20Hz.

the different BCI commands to complete all game levels succesfully with good scores in a self-paced asynchronous mode; to toggle between asynchronous mode and autopilot mode; and to tell the autopilot to plan and move the wheelchair to one of five geographical locations in the virtual world, all only by means of EEG brain waves.

Lower completion time of a game level is equivalent to better control of the brain-actuated wheelchair. A timer system was used that both displays the amount of time the user have spent in a GUI as well as stores the completion time in a high score system.

Two safety features were implemented, namely collision avoidance and rolling protection. Navigating the wheelchair, if suddenly on collision course with an object tagged as "collidable" (which is almost any object in the virtual environment), the safety brakes will engage if the wheelchair gets too close. In addition, brakes are also engaged to avoid unwanted rolling if the wheelchair's angle relative to the horizontal plane reaches a certain threshold and no control command is present.

The A* algorithm was used as basis both for path planning in the autopilot mode, and for simulating people walking around on streets.

Preliminary ANN experiment

To gain some insight into the acquired EEG data, a scatter plot of the signal amplitude of EEG channels 4 and 7 at 20 Hz for either "meditation" samples or "push" samples is depicted in Figure 11. The two cognitive states are not aggregated in clusters, which means that observing EEG at just one particular frequency generally is not sufficient for classification of a BCI command. It it is for this reason we had to use bands of frequency with mean power spectral density instead. As a matter of fact, running the ANN with a set of discrete frequencies proved to be insufficient for classifying the two EEG states. Instead, when running the ANN as described previously using the mean power spectral densities for six bands of frequencies, the ANN was able to consistently discern meditation from the "push" command with an error rate of 0–4%, depending on the initialisation values of the network, and the distribution of samples in the training, validation, and test sets.

Discussion

In this paper, we present a game-based learning framework for controlling brain-actuated wheelchairs. The framework may be used to train paraplegic patients with paralysis of the upper body in a safe virtual environment before introducing them to real wheelchairs. The virtual wheelchair is controlled only using brain waves through the low-cost COTS product Emotiv EPOC headset. Moreover, the virtual environment has been developed using the Unity 3D game engine. Compared to existing works, we use a game-based learning methodology to motivate, enhance and speed up the learning process. The framework is modular and flexible, with easy extensions to more features such as game levels and skill training, multiplayer options, interfacing to a real wheelchair, and more.

Safety and Control

Safety is an extremely important issue before actual real-world brain-actuated wheelchairs can be used. Here, we have implemented two safety features, namely collision avoidance and rolling protection. Collision avoidance would be much harder to do in a real-world, uncertain, dynamic environment than in our controlled virtual world, and would likely require the use of advanced artificial intelligence (AI) for computer vision, planning, and decision-making. Using the rolling protection mechanism for a real wheelchair would need a gyroscope but should be fairly easy to implement for the physical wheelchair.

A safety feature that probably should be implemented include some kind of AI emergency interruption, where the AI overrides the BCI command provided by the user if the execution of the command can be dangerous, such as driving the wheelchair into a street with heavy traffic.

It may also be that the inclusion of a third semi-autonomous, or cue-paced (synchronous), mode could improve control and thereby safety. In such a mode, the user is presented with cues such as a visual image, text, sound, or similar for triggering particular BCI commands. An AI decision-support system could infer what would be a good command at a given moment, for example, turning left at an intersection, and present the user with the cue that corresponds to turning left.

Finally, one could take advantage of the steady state visually evoked potential (SSVEP), much like we do in our accompanying paper submitted concurrently (Verplaetse et al., 2016). When providing a user with a computer screen rapidly switching between two colours at a given frequency, one can evoke a SSVEP for higher EEG activation and better mental control. According to a survey by Zhu et al. (2010), BCI systems based on the SSVEP provide a higher level of information throughput and require shorter training than BCI systems using that are not augmented with SSVEP. The SSVEP could be used in a manner similar as the cue-paced mode above to aid in generating certain EEG patterns and BCI commands at discrete points in time.

Reverse-Engineering Emotiv Software

The preliminary ANN experiment is equivalent to a first baby step towards reverse-engineering the proprietary software developed by Emotiv for generating BCI commands based on EEG signals. We were able to successfully implement a simple ANN able to classify two EEG states: meditation and "push." The experiment has provided some insight into how we can use ANNs for such brain wave pattern recognition. However, we acknowledge that there is still much work to do, and that the task we adopted was simple. If we had chosen two BCI commands that both require concentration and mental focus on a command (as opposed to meditation, which aims to reduce concentration), it may have been more difficult for the ANN to perform classification. Likewise, with more BCI commands to classify, the problem also becomes harder. Nevertheless, our experiment does seem to indicate that ANNs are suitable for solving this problem.

Future Work

As future work, it would be interesting to consider the possibility of adding some level of adaptability to the proposed game-based methodology to improve the learning experience. This could be achieved by developing a specific learning algorithm that can adapt the level of external assistance provided to the subject according to the subject's experience. A similar algorithm has been presented by several researchers (Philips et al., 2007; Millan et al., 2009). The underlying idea was to provide the subject with an adaptive level of support, thereby complementing the user's capabilities at any moment, whenever necessary. An inexperienced user will receive more assistance than an experienced one. If, after some time, the performance of the user has improved, the assisting behaviours will be less activated. By introducing this adaptability, the users remain in maximal control.

To make the game-based learning experience more immersive and therefore even more engaging for the user, the integration with an open-source low-cost framework for a fully-immersive haptic, audio and visual experience like the one proposed by Sanfilippo, Hatledal and Pettersen (2015) may be considered. This framework allows for establishing a kinesthetic link between a human operator interacting with a computer-generated environment.

One more possible future work that we are considering is the possibility of implementing a shared control system between the a simulated and a real wheelchair. The system can then serve the purpose as a platform for virtual prototyping of the real wheelchair, where modelling, features, functionality and so forth can be simulated before the real physical wheelchair is built. This approach may also be very useful for minimising the difficulties for the subjects to switch from a simulated system to a real system when the training programme is terminated. In addition, comparative studies can be performed concerning usability and taking into account human factors.

The concept of EEG and BCI can probably be beneficial for other human assistance technologies. One exciting application could be that of intelligent prostheses or exoskeletons that likely would require the use of machine learning algorithms and evolutionary computation, with which we have extensive experience at NTNU in Ålesund (e.g., see Sanfilippo et al., 2013, 2014; Sanfilippo, Hatledal, Styve, Zhang and Pettersen, 2015; Bye et al., 2015; Bye and Schaathun, 2015; Alaliyat et al., 2014; Hatledal et al., 2014, for work relating to genetic algorithms, particle swarm optimisation, ANNs, and more).

Other possible work to be considered in the future may include testing of different machine learning algorithms and compare their corresponding performances. In order to do this, a machine learning framework that provides a selection of existing learning approaches and allows for implementing new algorithms can be used as presented in (Hatledal et al., 2014). This framework can be used to develop a standard benchmark suite for testing and measuring the effectiveness and accuracy of the compared methods.

Finally, we would like to draw attention to an accompanying paper we submit concurrently, in which we use a similar system as described here, designed to provide partially monoplegic stroke patients with a rehabilitation platform using EEG brain control of a virtual paretic hand (Verplaetse et al., 2016).

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