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# BCI framework based on games to teach people with cognitive and motor limitations

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**Abstract**

Nowadays, Human-Computer Interaction (HCI) systems e.g. keyboard, mouse and touch screen are frequently used by anyone. However, those ways to interact with computers may be not suitable for disabled persons. Brain-Computer Interface (BCI) is an HCI system which can be used as an alternative for these persons. This approach allows operating a computer using only the brain signals, for instance, imagine a situation where a participant only needs to think about an action in order to make it happen: to move, to select an object, to shift gaze, to control the movements of their (virtual) body, or to design the environment itself, by "thought" alone.

In this paper we propose a BCI framework to process brain signals resulting from imagination processes that is used together with serious games to teach or improve autonomy of physically handicapped people. Two simple scenarios based on grasp and eye-gaze imagination games were developed to test the framework. Games consist on choosing the right object to put on the recycling bin or to choose a piece of a puzzle to fit the other one in a white board. Through the proposed approach we are able to discriminate the direction intended by the player. Our results show that we achieve about 80% of accuracy when a block of 30 seconds of imagination is considered.


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## 1. Introduction

Nowadays, Information Technology (IT) and IT-devices are all around us. They have various forms, like desktop, laptop, smartphones, PDAs, touch-screens and tablet PCs. The way to interact with these devices is called the Human-Computer Interaction (HCI). Currently, we have different types of HCI systems e.g. keyboard, mouse and touch screen. While these are all traditional systems, there are also some advanced forms of HCI system which are in developing state and have very promising features to revolutionize the IT industry by changing the way we access IT-devices.

Brain Computer Interface (BCI) can be considered an HCI system which is in developing state and has very promising features for revolutionizing the IT industry. Through the BCI we can control computers using brain signals and hence can develop next generation of ‘user-friendly’ systems.

Using online electroencephalogram (EEG) signals, Pfurtscheller & Neuper[1] showed that it is possible to identify a few mental processes using electrodes attached to the scalp. These mental sates results from the brain activity and can be transformed into control signals and associated to simple computer commands (e.g., cursor movement).

In this paper we explore the possibilities inherent in BCI with serious games, where people do not actually have to do anything physical to interact with and through a computer, but where the computer is directly attuned to their brain activity. For instance, imagine a situation where a participant only needs to think about an action in order to make it happen: to move, to select an object, to shift gaze, to control the movements of their (virtual) body, or to design the environment itself, by “thought” alone.

BCI and serious games are very useful for extensive training and may provide a very promising future for physically handicapped people, who cannot access traditional computer systems due to their physical disabilities. In this context we propose a BCI framework to process brain signals resulting from imagination processes to be used together with serious games to teach or improve autonomy of physically handicapped people. Two simple scenarios based on grasp and eye-gaze imagination games were also developed to test the framework. These two games consist on choosing the right object to put on the recycling bin (Fig. 1) or to choose a piece of a puzzle to fit the puzzle (Fig. 2).

Fig. 1. BCI-game based on Avatar’s gasp imagination.

Fig. 2. BCI-game based on Avatar’s gaze.

The remaining of the paper is composed by five sections. Section 2 discusses related methods and mechanisms used to integrate games and BCI in the context of learning for people with disabilities, mainly motor palsy. In sections 3 we propose a framework to process brain signals, discuss the BCI concepts, components and methodologies in order to create a full approach based on games. Section 4 reports results concerning the proposed methodology and games, while section 5 concludes the paper.

## 2. Related work

In this section we review works which address BCI systems and Virtual Reality (VR) specially designed for people with disabilities. These systems are related to daily task accomplishment, now possible through cerebral waves. Therefore, the works presented demonstrate the potential of new interaction forms with interactive systems through BCIs.

Ceccoti[2] developed an asynchronous BCI speller also based on Steady state visually evoked potential (SSVEP). The speller objective was to achieve an intuitive system where even inexperienced users could successfully use it, while causing the least possible discomfort. The letters are divided into groups and what flashes is the contour of those groups. The system automatically configures the BCI and the asynchronous nature of the interface leaves the user more relaxed. The work of Xu[3] proposes a web browser BCI application based on the same approach. The application allows searching in Google and inputting text. The work in Hood[4] reports a BCI control for a car driving virtual simulation. The BCI uses three LEDs as SSVEP stimulus, one to right steer the wheel, another one for left steering it, and the last for straight steering. It reached good precision rates but in the authors opinion, more tests must be done in virtual ambient to improve the interface and safety guarantees of future car-driving BCIs.

An interesting class of brain activity for game playing, mainly for people with disabilities, is related to motor imagery. That is, the user imagines a certain movement. For example imagining a left arm movement can be distinguished from imaging a right arm movement. This kind of mental simulation of movement can be measured and distinguished. It is not true only for arms, but also for eyes, feet or hand. The work reported by Poor[5] assess EPOC capacity in a BCI based on the imagination of kinetic actions. On the experiments the objective was to rotate a cube after an initial brain signal recording and calibration.

The work of Friedman[7] investigates BCI navigation in a cave virtual environment (VR) based on imagined movement. The VR environment consists of a street with people spread out and stores on the sides – those can be projected in stereo view shutter glasses for increased realism and experience. To walk, the users have to imagine their own feet moving, while head rotation – tracked through an accelerometer – is used for changing walking direction and imagined hands movement – to pass the impression of "touch" – is used for interacting with other persons on the street. The virtual people remain at still until the user interacts with them. In that instant, they start to walk to indicate interaction success.

In those applications it has been shown that BCI approaches are reliable. However all of those applications were designed to be used in entertainment technologies. In our proposal we intent to create a platform that can support different king of games used to teach or train children with disabilities. It allows us to design new games, game environments, and exertion interfaces that are controlled by motor disabled people using their brain activity.

## 3. BCI Framework to Teaching Children with Motor Limitations

Taking into account the motor limitations of some children, and the advance of technology, this work aims to propose a new learning paradigm based on imagination and electroencephalogram (EEG) measurements of brain signals. The big challenge is to identify the intention of the players/children and translate it in commands to control anything connected to the real world (BCI).

Many communication devices (e.g. mouse, keyboards, joysticks), which depend on muscle movements, are not feasible for many children with motor limitations. Those children need a different communication channel, independent of the motor activity. In order to create new teaching mechanisms for those children, a BCI games based on grasp imagination was developed.

The first game consists on choosing the right object to put on the recycling bin. One of three colored baskets (blue, yellow and green) and two different objects are shown to the player and he/she must choose the most appropriated object for that basket (Fig. 1). His/her choice is indicated by the imagination of the avatar to grasp the selected object. The second game is based on eye-gaze imagination. In this scenario, a piece of a puzzle and two other pieces are shown to the player and he/she must select the right piece to fit the puzzle (Fig. 2). Similar to the first game, the selection of the piece is done by imagination of the avatar looking at the selected piece (one at each side of the avatar – left and right sides). Fig. 3 show the architecture built to play those games.

Using a BCI to control serious games raises several issues: when the classification of "thought" must be done, the number of input classes used and the nature of the mapping between imagery and resulting action in the game. In order to limit the number of input classes, there are just two choices in each scene. Concerning the mapping between the imagination and the resulting action in the game, the avatar does the arm movement according to the result of pattern classification of imagination. At the end, when the player chooses the right option, the avatar introduces the chosen object in the basket and a small excerpt of a song is played.

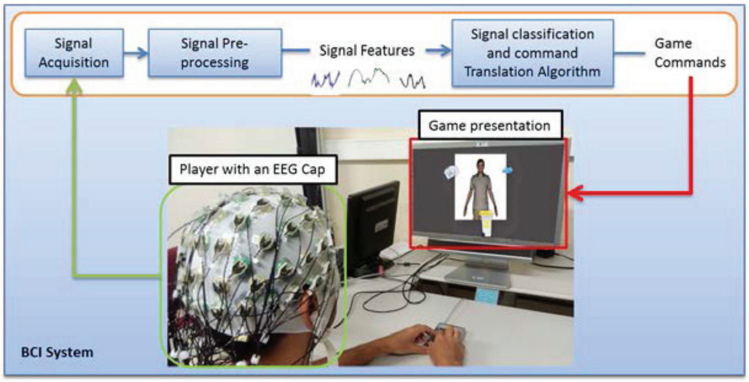



Fig. 3. BCI setup.

## 3.1. Methodology

**Game presentation:** game scenes are presented on a 15in computer monitor, located at a distance of 70 cm from the participant. The game is controlled by a personal computer, which runs an in-house developed virtual reality application (Vizard application[8]).

For each game session, a randomized game scene order is generated. Children are told to keep their eyes focused on the avatar (nose) and to avoid movements or blinking as much as possible. In order to track eye movements or micro-saccade, an eye tracker system is used (iViewX[9]). The eye tracker data is used to discard part of the EEG signal where eye movement occurs. The player is further instructed to imagine the avatar's eyes or upper limbs (depending on the game) to move to a specific target object.

The number of scenes, target objects and level of difficulty are defined by the teacher or care giver, previously, and must take into account the level of knowledge of the player.

EEG and EOG Recording: The EEG data is recording using an actiCHamp amplifier[10] with 64 electrodes mounted in an electrocap. The 10-20 international system[11] is used, electrodes were referenced to left ear lobe and electrode impedance was kept below 15 kΩ. All signals are filtered with a low-pass filtered at 100 Hz, digitized with a sample frequency of 1000 Hz, and digitally stored for off-line analysis.

Horizontal and vertical eye movements are also stored using Electrooculogram (EOG) and an Eye Tracking. In both, EEG and eye tracking data, specific makers are used to correlate the data.

**Training:** After attachment of the EEG cap, the player will be instructed to complete a block of practice trials to make sure he/she understood the instruction and to familiarize him/her with the game and procedure, as well as to train the BCI models in order to achieve a good level of classification.

In the training, we used the EEGLab toolbox[12] with some modifications and appropriate configurations to pre-process data. The pre-processing approach consists on applying band-pass and notch filters, as well as re-referencing data to an average reference.

In order to evaluate the brain response, signal segmentation is performed to identify common patterns. Two patterns are used, one for each left and right sides. Afterwards, a baseline correction mechanism is applied to the signal and unwanted segments (bad segments) are removed. Fig. 4 shows the algorithm used to process the segmentation, mark unwanted segments and remove them from the training data. These unwanted segments are removed when muscular or swallowing noise is identified in a set of electrodes.

Considering $M$ a set of markers used to identify specific events during the training, the algorithm starts by creating a set of segments $S$, where each segment corresponds to an interval around the marker $m$. In our experiments we used 0.5 s as pre-stimuli time and 11 s as post-stimuli. $t_m$ represents the instant of the marker in the raw signal.

Once processed the segmentation, the algorithm compares each segment of $S$ with a set of patterns $P$ in order to reject unwanted segments. This set of patterns $P$ is defined based on known patterns like muscular or swallowing movements, common described as artefacts in the literature.

```
for each m ∈ M
        S = Signal([t_m − t_pre_stimuli   t_m + t_pos_stimuli]);
end

for each s ∈ S
        for each p ∈ P
                if p fits s
                        s is marked to be removed;
                end
        end
end
remove marked segments from S
```

Fig. 4. Segmentation and data cleaning algorithm.

In order to identify which segments are marked to be removed, the algorithm compares the pattern $p$ with part of the segment $S$. If 80% of the points of $p$ are coincident with that part of the segment $S$ or show a difference up to 10 % of amplitude of the signal, that segment is marked to be removed. At the end of this procedure, the algorithm removes the marked segments.

Afterwards, an independent component analysis (ICA)[14] is performed to identify and remove other sources of noise, such as blinks.

Once concluded the pre-processing of the EEG signal, a classification model is needed to identify patterns in the signal, and to discriminate the intention of the player (selection of left or right objects).

**Feature Extraction:** Considering the EEG signal resulting from the pre-processing approach, the signal processing approach used during the training phase consists on extracting the most important features of the signal. These features can be the signal wave itself, the amplitude of the signal, the power within a specific band of frequencies or other property of the signal.

Since our data was recorded using 64 channels, a survey over all channels must be performed in order to identify which channels are more suitable for feature extraction. According to the literature and based on the type of interaction chosen (imagination of arm movement), the most important electrodes should be concentrated on motor area[15, 16]. In our experimental setup, we verify that all important electrodes are in this area.

Once the set of electrodes that will be used is identified, the set of features used to define the classification model is composed by the chosen feature itself (signal wave, amplitude of the signal, power within a specific band of frequencies, other property of the signal or a combination of properties) for that set of electrodes.

After having defined the set of electrodes and features, a PCA algorithm is applied to rank each feature. This raking allows discriminating which features are more important to the classification. It also allows reducing the number of features by dropping the less important ones, which makes the classification model faster and more reliable to be applied in real-time.

In this work, the band power was calculated in the high alpha, low beta (10–20 Hz) band, over last 10 second. Band power measures the total power within any specified frequency range or band. If there are N data frequencies in the sequence, then the power of the band can be computed as[17]:

$$Power_{Band} = \frac{1}{N} \cdot \sum_{k=1}^{N} \left[ \left( A_{signal}(k) \right)^2 - \left( \overline{A_{Baseline}} \right)^2 \right]$$

Where $A_{signal}(k)$ represents the amplitude of signal at frequency $k$, $N$ corresponds to the number of points (frequencies) between $f_{low}$ (low bound of the frequency band) and $f_{high}$ (high bound of the frequency band) and $\overline{A_{Baseline}}$ represents the average amplitude of signal at the baseline.

**Online Classification:** in order to identify the intention of players, an online classification of the EEG signal is done. Fig. 6 also includes the online classification diagram. Upon receiving a new trial (EEG signal collected during a specific period of time), the feature extraction method explained before is applied. The resulting features were classified with Support Vector Machine (SVM) and transformed into a control signal.

A SVM uses a discriminant hyperplane to identify classes[20]. The selected hyperplane is the one that maximizes the distance from the nearest training points. SVM classifier has been applied, always with success, to a relatively large number of synchronous BCI problems[21-23].

## 4. Experimental Evaluation

Based on the approach described in section 3 and in the two games proposed, a pilot experiment was done by recording the electroencephalogram data while a subject plays the games.

Electrodes were placed according to the 10-20 system for recording homologous channels of EEG data from the left and right hemispheres referenced to the left ear lobe. Each game ran around half an hour during the training phase. Twenty one valid segments of 10 seconds per condition (left and right) were collected and used to define the classification model. Afterwards, each segment was divided by three, resulting in a total number of 63 trials per condition. Each trial corresponds to a 3.33 ms of imagination.

Since 64 channels were used to record the EEG signal, before training the SVM model, we did a survey to identify which electrodes should be used to classify the intentions of player according to the game roles. From this survey, we conclude that the relevant electrodes for game 1 (imagination of grasping an object) are FC3, FC4, FC5 and FC6, while CP1, CP2, CP3 and CP4 are the most relevant for game 2 (imagination of looking at an object).

Once selected the set of electrodes and considering the nature of games (imagination), time-frequency plots of training data were created for each electrode. Since the proposed approach, in section 3, is based on features such as band power, the most suitable frequency bands for classifications were selected and the average band power was determined. Fig. 6 and Fig. 7 show four time frequency maps and the chosen frequency band for each game.

As referred in the literature[15-18] μ-rhythms are associated with movement planning. Therefore, we concentrated our study around those frequencies (highlighted frequencies in Fig. 6 and Fig. 7). As we can see, those frequencies show different levels of power for left and right intentions of movement, which allows discriminating which direction is intended.

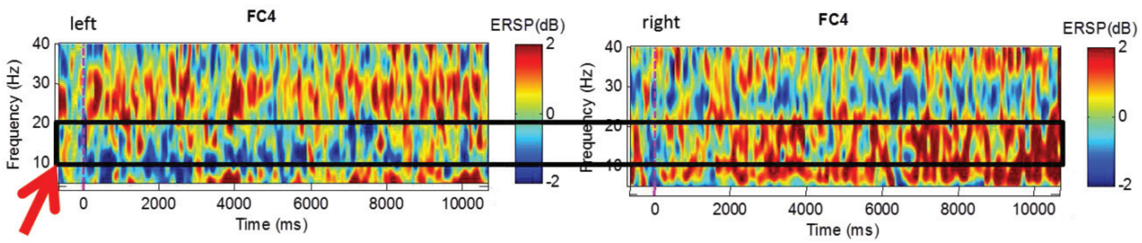



Fig. 5. Time-frequency map of FC4 left and right conditions for game 1.

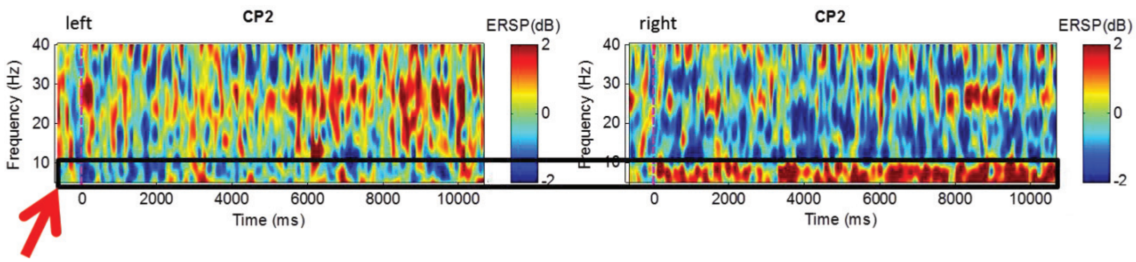
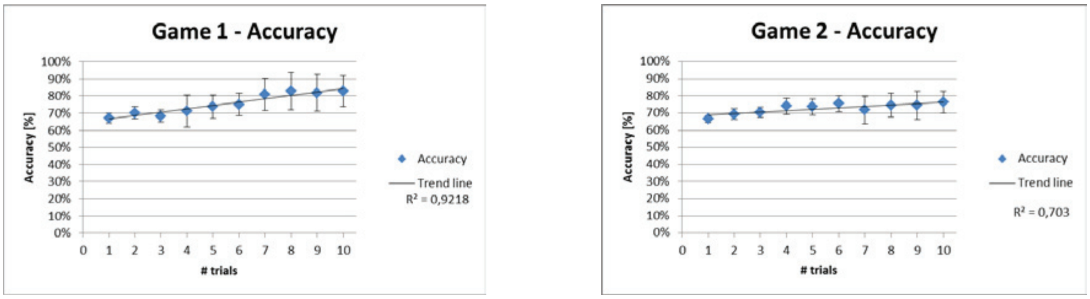



Fig. 6. Time-frequency map of CP2 left and right conditions for game 2.

Upon defining the set of electrodes and frequency bands, the feature extraction approach is applied and the SVM training model is defined. In order to test the SVM model, a cross-validation approach with 5 folds is also applied. In this step, the training data is shuffled, part of the data is selected to test the classifier and the classification model is tested. Fig. 8 show the accuracy resulted from the classification. Single-trial and multi-trial classifications were tried. For multi-trial classification, the number of trials included in each mean varies from 2 to 10.



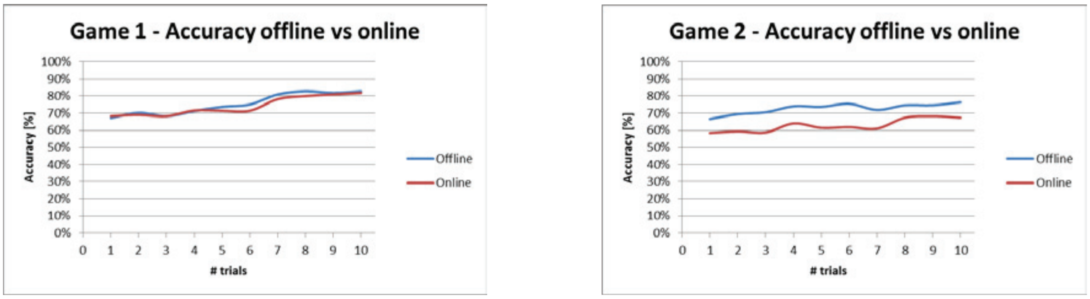

a) Game 1 b) Game 2

Fig. 7. Classification accuracy

From Fig. 8, we can conclude that classification accuracy is less than 70% when a single-trial classification is done. However, if a moving average of last 5 trials was considered, in both cases the accuracy rises to 76% and shows a reduced standard deviation (about 5%). As shown in Fig. 8, the results keep improving when more trials are used for classification. As we can see through the trend line, if the number of trials increases, the accuracy also increases, following an approximated linear trend.

Since the goal is to build a BCI system used to teach children with motor limitations, Fig. 9 show the obtained accuracy for offline and online classification. The offline classification results concern the accuracy obtained from training dataset when the model was tested. The online classification was obtained in real time from the player intentions when he/she is playing the game.

From Fig. 9 we can see that online classification shows lower accuracy when compared with offline classification. The difference between offline and online results can be neglected for game 1, while it shows higher values for game 2. The difference obtained for game 2 may be due to ocular artefacts. Those artefacts are removed when the offline classification is done, because an ICA algorithm is applied. This ICA algorithm is not applied during online classification because it introduces high computational complexity, which causes a high processing time.




a) Game 1 b) Game 2

Fig. 8. Accuracy for offline and online classifications

Another important issue in BCI systems and classification algorithms is related with the time to detect the intention of the player. The proposed approach takes, in the training phase, between 7 and 9 seconds to extract and create the SVM model and up to 100 ms to classify a set of trials (up to 10).

## 5. CONCLUSIONS

In this work we proposed a framework for human-computer interaction based on brain-computer interface. It allows processing brain signals used in serious games to teach or improve autonomy of physically handicapped persons. Two scenarios based on grasp and eye-gaze imagination games were developed to test the framework. The proposed approach allows discriminating the direction intended by the player. The results show that about 80% of accuracy is achieved when a block of 30 seconds of imaginations is considered. Moreover, the processing time is reasonable in training phase and it shows good results during the classification in both cases (offline and online).

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