Goal-Oriented Control with Brain-Computer Interface

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Abstract. A brain-computer interface (BCI) is a new communication channel between the human brain and a digital computer. Such systems have been designed to support disabled people for communication and environmental control. In more recent research also BCI control in combination with Virtual Environments (VE) gains more and more interest. Within this study we present experiments combining BCI systems and VE for navigation and control purposes just by thoughts. Results show that the new P300 based BCI system allows a very reliable control of the VR system. Of special importance is the possibility to select very rapidly the specific command out of many different choices. The study suggests that more than 80% of the population could use such a BCI within 5 minutes of training only. This eliminates the usage of decision trees as previously done with BCI systems.

Keywords: Brain-computer interface, virtual reality, P300 evoked potential.

1 Introduction

A Brain-Computer interface (BCI) is a new communication channel allowing subjects to interact with a computer without using any muscle activity. Such a system represents an additional output channel without relying on the brain's normal pathways of muscles or peripheral nerves [1, 2]. A BCI converts specific brain signals into control commands using pattern recognition methods. In order to properly operate a BCI, the system is firstly trained on subject specific brain activity data.

Brain-computer interface systems have been developed during the last years for people with severe disabilities to improve their quality of life. Applications of BCI systems comprise the restoration of movements, communication and environmental control [1-3]. However, recently BCI applications have been also used in different research areas e.g. in the field of virtual reality [4, 5]. There the control of and navigation in smart homes via BCI interfaces can be studied before realizing the real world smart home environment.

Non-invasive BCI systems have been successfully realized based on different brain electrical signal (electroencephalogram, EEG) phenomena:

Between 1 and 5 degrees of freedom of control have been realized up to now for slow cortical potentials [1]. Steady-state visual evoked potentials [6;7] allow mostly

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up to 12 different decisions and are only limited by the number of distinct frequency responses that can be analyzed in the EEG. This approach uses the fact that flickering light sources with flickering frequencies in the range of around 8-20 Hz induce brain oscillations of the same flickering frequency. Applications so far comprise e.g. robot or mobile phone control [8].

BCI systems based on induced oscillations use mostly motor imagery strategies to generate event-related de-/synchronization (ERD/ERS) in the alpha and beta frequency ranges of the EEG [5, 9] This type of BCI was realized for cursor control on computer screens, for navigation of wheelchairs or in virtual environments [5]. About 2-4 degrees of freedom for control can be realized so far. However, it remains the case that the highest information transfer rates are reached with only 2 decisions beyond which the accuracy falls dramatically.

A P300 based BCI system uses the effect that an unlikely event induces a P300 component in the EEG, i.e. a positive deflection in the EEG signal is occurring around 300 ms after the event. Such systems are suited for spelling device, because a high number of different target characters enhance the BCI communication speed [7, 10, 11]. However, recently BCI interfaces in e.g. Japanese language using up to 72 letters have also been reported [12].

In a spelling application characters or icons are ordered in rows and columns on the computer screen. There exist two different strategies to realize the P300 speller: (i) the row /column (RC) speller highlight multiple characters at once and the single character (SC) speller flashes each character individually.

Therefore a higher P300 amplitude and more reliable control can be expected with the SC flasher because it is more unlikely that the target character appears. Sellers found that a 3 x 3 matrix had higher accuracy than a 6 x 6 matrix, but a lower communication rate. With an inter-stimulus interval (ISI) of 175 ms and a 3x3 matrix Sellers achieved an accuracy of 88 % in the best case [11].

This study is divided into two parts:

Firstly, we were interested in how many people could use such a P300 based BCI interface at all. A similar study based on motor imagery has proven that around 6 out of 100 naïve subjects participating in a 6 month lasting study setup during a public fair could control a BCI immediately after only 20 minutes of training [13]. Therefore, it was interesting if a similar percentage of the population could use such a P300 control in the single character study.

Secondly, as P300 control allows using rather high degree of freedoms compared to motor imagery based BCIs, a virtual smart home P300 control interface was designed. Here it was of interest if subjects could also control a more complicated interface with high accuracy and speed in the virtual smart home study.

2 Material and Methods

A total of 41 naïve subjects participated in the study. 38 subjects participated in the first study to determine the accuracy of a P300 control by investigating a larger population of subjects. 3 subjects participated in the second experiment for controlling a virtual smart home environment.

The subjects were seated in front of a laptop computer and were instructed not to move and to keep relaxed. Fig. 1B yields the electrode configuration with 8 EEG derivations used for the study. Typical P300 evoked response data for a target from one subject are overlaid at the corresponding electrode positions. The EEG data were acquired with g.USBamp (24 Bit biosignal amplification unit, g.tec medical engineering GmbH, Austria) and 256 Hz sampling frequency. The ground electrode was located on the forehead; the reference was mounted on the right ear lobe. EEG electrodes were made of gold or sintered Ag/AgCl material.

For both experiments the SC speller was selected as for the smart home environment also non quadratic display matrices were developed.

2.1 Single Character Study

Fig. 1A shows the setup for the SC speller. A total of 36 characters and numbers (A, B, … Z; 0, 1, … 9) are displayed in a quadratic matrix on the computer screen. The SC speller highlights each character individually for 60 ms. Between the flashes there is a short dark time of 40 ms where nothing is flashing up. The subject has now the task to look at the character he/she should spell and count how many times the character flashed up. This helps the person to be concentrated on the task. After 15 flashes of each character the signal processing unit calculates the evoked potential and performs a classification to find the character that the subject investigated. Then the flashing sequence starts again and the subject has to look at the next character. The BCI system must be trained firstly on individual EEG data and therefore the subjects were asked to sequentially “write” (or look at) the 5 characters ‘W’, ‘A’, ‘T’, ‘E’, and ‘R’. This process took about 5 minutes.

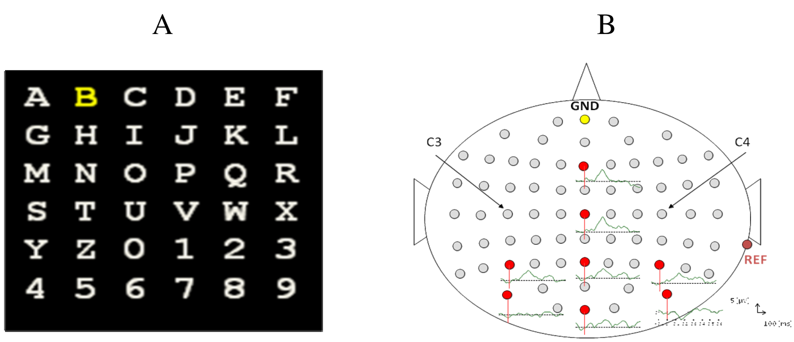

Fig. 1. panel A: Screen layout for the 36 characters; panel B: Top view of head and electrode setup for P300 experiment. The nose is pointing to the top of the page. Electrode (from top left to bottom right indicated as dark shaded disks) positions Fz, Cz, P3, Pz, P4, PO7, Oz and PO8 are used. A typical P300 evoked potential for a target response averaged across 15 trials is indicated near the corresponding electrode positions.

Then the BCI system was trained on the EEG features based on a linear discriminant analyzer (LDA). In the next run the subject had to spell the word ‘LUCAS’ which took again around 5 minutes.

The Simulink model shown in Fig. 2 is used for the real-time analysis of the EEG data. The *g.USBamp block* reads in the data from the 8 EEG channels. Then data are band pass filtered between 0.5 and 30 Hz in the *Filter block* and down-sampled from 256 Hz to 64 Hz in the *Downsample block* . The S*ignal Processing block* calculates the evoked potentials and performs further averaging across time points and data reduction. A total of 12 feature values per P300 evoked potential is sent to a linear discriminant analyzer for classification. The *Scope* and *To File blocks* are used to visualize the EEG data and to store it for later off-line analysis. The whole Simulink model is driven by the *g.USBamp* hardware block which ensures that the model is updated every 1/256 s. The *Impedance Check block* is utilized to ensure low impedance values for the EEG electrodes.

The *Single Character Speller block* controls the experiment and highlights the corresponding characters randomly. It sends also an identifier *ID-Flash* of the flashing character to the *Signal Processing block*. The *Signal Processing block* generates a buffer for each character and stores the incoming EEG data 100 ms before and 700 ms after the flash occurred (800 ms epoch). This is done until 36 buffers are filled with 15 epochs (15 flashes of each character). Finally an LDA is used to classify the EEG data and to find the buffer closet to the trained P300 response. This classification result yields the character that the subject mentally selected and it will be displayed on the computer screen. Then the next character can be selected by the subject. For offline analysis the time of the *Flash* onsets and the *ID-Flash* of each flashing character are stored.

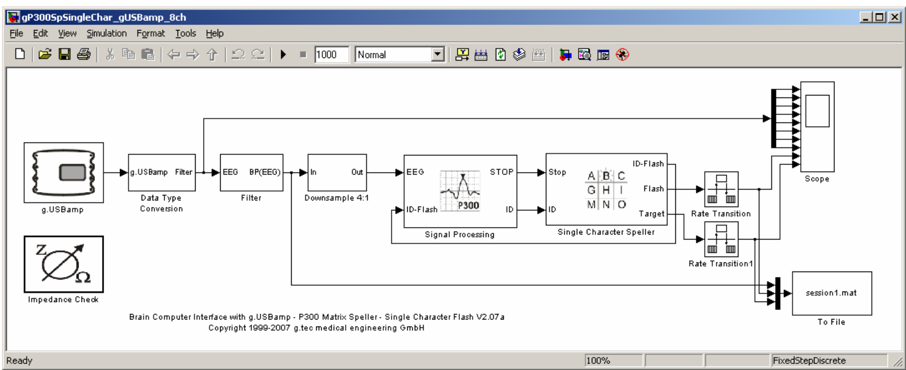

Fig. 2. Simulink model P300SpSingleChar_gUSBamp for the Single Character Speller. See text for the explanation of the different blocks.

2.2 Virtual Smart Home Study

Three subjects participated then in the experiments for smart home control. The electrode setup and recording details were not changed. At the beginning of the experiment the BCI system was trained based on the P300 response of 42 characters of each subject with 15 flashes per character (about 40 minutes training time). All 3 subjects needed between 3 and 10 flashes (mean 5.2) per character to reach an accuracy of 95 % for the single character speller. This resulted in a maximum information transfer rate of 84 bits/s for the single character speller.

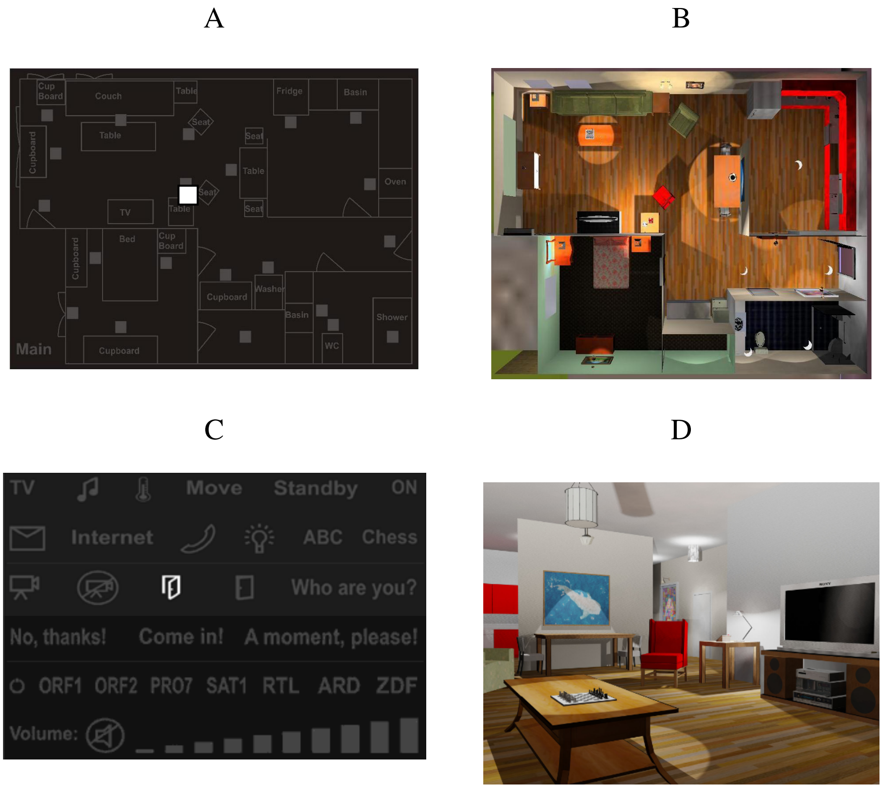

Fig. 3. panel A: Bird view of the apartment; the subject concentrates to the little blinking square at the table to go to the living room; panel B: Bird view of the virtual apartment representation; panel C: Control mask for selecting and controlling features from the TV set; panel D: 3D view of the living room

In the experiment it should be possible for a subject to switch on and off the light, to open and close the doors and windows, to control the TV set, to use the phone, to play music, to operate a video camera at the entrance, to walk around in the house and to move him/herself to a specific place in the smart home. Hence the P300 based BCI system was connected to a Virtual Reality (VR) system. A virtual 3D representation of a smart home with different control elements was developed based on the XVR environment (eXtreme Virtual Reality, University of Pisa). Fig. 3A and 3B yield a bird view of the apartment layout. The upper left panel represents the user interface. The small squares are flashed on and off in a random manner similar to the SC spelling interface. Here the user selected to be set to the living room in a goal orientated way and then selected to operate the TV set. The upper right panel gives the actual representation of the virtual smart home environment. Fig. 3C yields the control masks for controlling the TV set. Fig. 3D yields a 3D view of the living room. The Simulink model in Fig. 4 controls the virtual smart home. The main difference to model *P300SingleCharacterFlash* mode can be found in *Control Flash Smart Home block*.

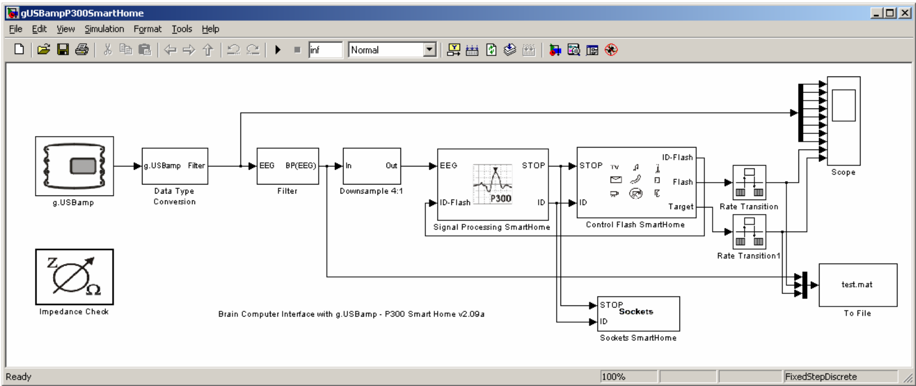

Fig. 4. Simulink model gUSBampP300SmartHome for controlling the virtual environment. See text for the explanation of the different blocks.

The *Control Flash Smarthome block* controls the experiment and highlights the corresponding icons randomly. It sends also an identifier ID-Flash of the flashing icon to the *Signal Processing Smarthome* block. Similar to the single character speller block the signal processing block generates a buffer for each icon and stores the incoming EEG data. Finally an LDA is used to classify the EEG data and to find the buffer closest to the trained P300 response. This classification result yields the icon that the subject mentally selected. This icon represents also the control command for the virtual environment and the command is sent via a the *Sockets SmartHome* block to the XVR smart home representation on a separate PC. Then the next icon can be selected by the subject. For offline analysis the time of the Flash onsets and the Target icon is stored for training of the LDA classifier.

3 Results

3.1 Single Character Study

From all sessions done by the 38 subjects, 55% of the subjects could use the SC speller immediately with 100% accuracy. This means all 5 characters of ‘LUCAS’ were written correctly. In 76% of the sessions the subjects had only 1 mistake. It must be noted that this is an on-line results and not a cross-validation result. Only in 2.5% of the sessions the subjects were not able to spell a single character correctly. All subjects participated also in a RC study. Results from a RC to SC speller comparison and results from an accompanying questionnaire will be published elsewhere. So the overall accuracy was > 80%.

3.2 Virtual Smart Home Study

Table 2 displays the results of the 3 subjects for the 3 parts of the experiment and for the 7 control masks. Interestingly, the light, the phone and the temperature mask were

Table 1. Percentage of sessions which were classified with certain accuracy. Results based on data from 38 subjects for the single character speller are depicted.

Classification Accuracy in [%]	Percentage of Sessions [N=38]
100	55,3
80-100	76.3
60-79	10.6
40-59	7.9
20-39	2.6
0-19	2.6
average accuracy of all subjects	82

Table 2. Accuracy of the BCI system for each part and control mask of the experiment for all subjects

Mask	Part1	Part2	Part3	Total
Light	100%	100%	100%	100%
Music	-	89,63%	-	89,63%
Phone	-	100%	-	100%
Temperature	100%	-	-	100%
TV	83,3%	-	-	83,3%
Move	88,87%	-	93,3%	91,1%
Go to	100%	-	88,87%	94,43%

controlled by 100 % accuracy. The Go to mask was controlled with 94.4 % accuracy. The worst results were achieved for the TV mask with only 83.3 % accuracy.

Table 3 displays the number of symbols for each mask and he resulting probability that a specific symbol flashes up. If more symbols are displayed on one mask, then the probability of occurrence is lower resulting in increased amplitudes of the P300 responses which should be easier to detect. The flashes column shows the total number of flashes per mask until a decision is made. The translation time per character that is longer if more symbols are on the mask.

Table 3. Number of symbols, occurrence probability per symbol, number of flashes per mask (e.g. 25 x 15 = 375) and conversion time per character for each mask

Mask	Symbols	Propability	Flashes	Time per character [s]
Light	25	4	375	33.75
Music	50	2	750	67.50
Phone	30	3.3	450	40.50
Temperature	38	2.6	570	51.30
TV	40	2.5	600	54.00
Move	13	7.7	195	17.55
Go to	22	4.5	330	29.70

4 Discussion

4.1 Single Character Study

This study showed that the P300 spelling device works with a very high accuracy after only 5 minutes of training. 72.8 % of the subjects were able to spell immediately with 100 % accuracy with the RC speller. This can be compared to an earlier study performed with 99 subjects and motor imagery in Graz [13]. The subjects had to imagine left and right hand movement (20 times each) to move a cursor on the screen to the corresponding side. Then the BCI system was trained on this EEG data (recorded from positions C3 and C4). The training time was also around 6 minutes and the recursive least square or band power estimation in predefined frequency bands with LDA were used for classification. 6.2 % were able to reach accuracy between 90 - 100 % as shown in Table 2. This is well below the P300 results achieved in this study. Of course the motor imagery BCI worked only with 2 bipolar derivations compared to 8 EEG electrodes for the P300 experiment, but the assembly time is almost equal**.**

4.2 Virtual Smart Home Study

The P300 based BCI system was successfully used to control a smart home environment with accuracy between 83 and 100 % depending on the mask type. The difference in accuracy can be explained by the arrangement of the icons.

However, the experiment yielded 3 important new facts: (i) instead of displaying characters and numbers to the subject also different icons can be used, (ii) the BCI system must not be trained on each individual character, (iii) from all experiments a grand average classifier was built and tested in selected subjects. In contrast to motor imagery BCIs were the system must be retrained every time it is used, the P300 approach can use a standard classifier. The BCI system was trained with EEG data of the spelling experiment and the subject specific information was used also for the smart home control. This allows using icons for many different tasks without prior time consuming and boring training of the subject on each individual icon. This reduces the training time in contrast to other BCI implementations were hours or even weeks of training are needed [1, 2, 3]. This reduction in training time might be important for locked-in and ALS patients who have problems with the concentration over longer time periods. The P300 concept works also better if more items are presented in the control mask as the P300 response is more pronounced if the likelihood that the target character is highlighted drops down [4]. This results of course in a lower information transfer rate, but enables to control almost any device with such a BCI system. Especially applications which require reliable decisions are highly supported. Therefore the P300 based BCI system enables an optimal way for the smart home control. The virtual smart home acts in such experiments as a testing installation for real smart homes.

Also wheelchair control, which many authors identify as their target application, can be realized with this type of BCI system in a goal oriented way. In a goal oriented BCI approach it is then not necessary e.g. to move a robotic hand by thinking about hand or foot movements and controlling right, left, up, down commands. In a more natural way humans just think “I want to grasp the glass” and the real command is initiated by this type of BCI implementation.

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