Brain-Computer Interface for Virtual Reality Control

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Abstract. An electroencephalogram (EEG) based brain-computer interface (BCI) was connected with a Virtual Reality system in order to control a smart home application. Therefore special control masks were developed which allowed using the P300 component of the EEG as input signal for the BCI system. Control commands for switching TV channels, for opening and closing doors and windows, for navigation and conversation were realized. Experiments with 12 subjects were made to investigate the speed and accuracy that can be achieved if several hundred of commands are used to control the smart home environment.

The study clearly shows that such a BCI system can be used for smart home control. The Virtual Reality approach is a very cost effective way for testing the smart home environment together with the BCI system.

1 Introduction

An EEG based Brain-Computer Interface (BCI) measures and analyzes the electrical brain activity (EEG) in order to control external devices. BCIs are based on slow cortical potentials [1], EEG oscillations in the alpha and beta band [2, 3], the P300 response [4] or steady-state visual evoked potentials (SSVEP) [5]. BCI systems are used mainly for moving a cursor on a computer screen, controlling external devices or for spelling purposes [2, 3, 4].

BCI systems based on slow cortical potentials or oscillatory EEG components with 1-5 degrees of freedom were realized up to now. However, high information transfer rates were reached based on 2 degrees of freedom as otherwise the accuracy of the BCI systems dropped down. SSVEP based systems allow selecting up to 48 different targets and are limited by the number of distinct frequency responses that can be analyzed in the EEG. P300 response based BCIs typically used a matrix of 36 characters for spelling applications [4].

In a previous BCI study three subjects participated in a spelling experiment and were trained firstly in spelling characters and numbers based on their P300 EEG response [6]. Therefore, the characters of the English alphabet (A, B,...Z) and Arabic numbers (1, 2, ...9) were arranged in a 6 x 6 matrix on a computer screen. Then the characters were highlighted in a random order and the subject had the task to concentrate on the specific character he/she wanted to spell. All experiments were undertaken in 2 modes: (i) the row/column speller – all items of one row or column are highlighted at the same time, (ii) the single character speller – only one character is highlighted. For the single character speller each character was highlighted 15 times. For the

row/column speller each row and each column was also highlighted 15 times. This results in a speed up of 3 for the row/column speller. Therefore 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 and between 4 and 11 flashes (mean 5.4) for the Row/Column speller. This resulted in a maximum information transfer rate of 84 bits/s (60 ms per character flash time) for the single character speller and 65 bits/s (100 ms per character flash time) for the row column speller.

Based on this previous study this work shows the usage of a P300 based BCI system to control a smart home environment. The usability of the BCI implementation will be tested to control many different elements of a house. Of special interest was to test the accuracy of different control masks in the smart home application.

2 Methods

The smart home environment was implemented in XVR (extreme VR, University of Pisa) as Virtual representation of a real one and the P300 based BCI system was connected to it. The virtual 3D representation of a smart home with different control elements is shown in Figure 1.



Figure 1: Virtual representation of a smart home

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 location in the smart home. Therefore special control masks for the BCI system were developed containing all the different necessary commands. In total 7 control masks were created: a light mask, a music mask, a phone mask, a temperature mask, a TV mask (see Figure 2, left), a move mask and a go to mask (see Figure 2, right).

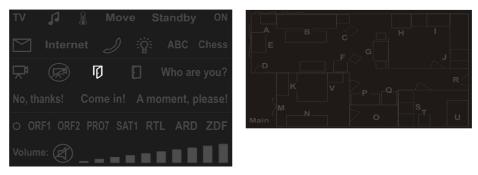


Figure 2: Left: Control mask with the main menu in the first 2 rows, the icons for the camera, door control and questions in the 3rd and 4th row and the TV control in the last 2 rows. Right: Control mask for going to a specific position in the smart home. The mask gives a bird's eye view of the apartment with characters at specific positions.

12 subjects participated in the experiments and were trained firstly on selecting specific commands from the P300 matrices. Each person had to select 7 icons of each of the 7 control masks for training the computer system on its individual EEG data. Therefore the characters were highlighted in a random order and the subject had the task to concentrate on the specific character he/she wanted to spell. All experiments were undertaken in a so called single character speller mode where only one character is highlighted at one specific time point. In order to increase the recognition accuracy it is necessary to highlight each character several times. In this experiment we tested the system with 8, 4 and 2 flashes of each character to test the accuracy and speed that can be achieved.

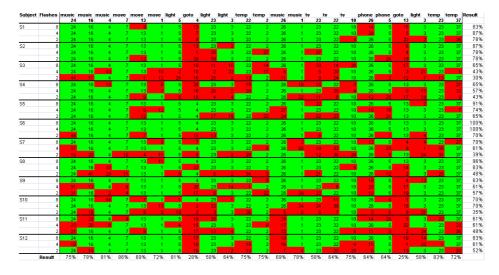
Another important parameter in the P300 experiment is the flash time (character is highlighted) and the dark time (time between 2 highlights). Both times should be as short as possible to reach a high communication speed, but must be long enough so that the subject can detect the flash and that the single P300 responses are not overlapping.

The training with 7 characters per mask took about 45 minutes and based on this data the BCI system was trained to recognize the specific EEG response. The experiment for the P300 smart home control was divided into 23 decisions involving all 7 control masks. One task was e.g. to go to the living room, to switch on the TV and to select a specific channel, ...

3 Results

Table 1 shows the results of the 12 subjects for the 23 decisions and 8, 4 and 2 flashes. The best result was achieved for subject S6 with 100 % accuracy for 8 and 4 flashes. The worst results had subject S3 with only 30 % accuracy for 2 flashes. All subjects performed best for the move forward command (id 7, 86 % accuracy) and worst for the goto command (id 13, 25 % accuracy).

Table 1: Classification results of the BCI based system for all subjects and all decisions. The first row show the mask and the second row the id of the decision that should be done. Then for each subject a correct decision is indicated in green color and a misclassification in red color for 8, 4 and 2 flashes per character.



Therefore it is interesting to compare the different masks for all subjects. Figure 3 shows the accuracies for all 7 masks. The light mask was used in the experiment for example 4 times and the total accuracy was 65,28 %. The best accuracies were achieved for the Music, Move and Temp masks. Clearly the worst accuracy had the GoTo mask.

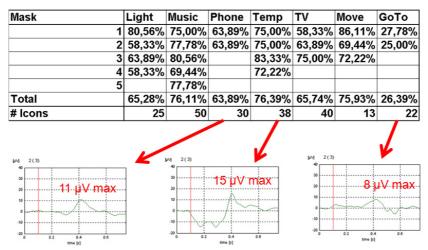


Figure 3: Accuracy for different masks for all subjects and number of icons on each mask. The last row shows the P300 evoked potential for three masks.

Therefore the P300 component was calculated for three masks. The P300 of the Temp mask reaches an amplitude of about 15 μ V, the P300 of the Phone mask reaches 11

 μV and the GoTo mask only 8 $\mu V.$

4 Discussion

The P300 based BCI system was successfully used to control a smart home environment with an accuracy of 79 % for 8 flashes, an accuracy of 70 % for 4 flashes and 54 % for 2 flashes for all subjects. The accuracy was of course higher if each item flashed up more often. But it was necessary to test the achievable speed since we already knew that the P300 BCI system can be controlled with very high accuracy using 15 flashes [6].

S6 was able to control the system with 100 % accuracy even with only 7 training icons per mask. Even the worst subject S11 still achieved an accuracy of 61 % with 8 flashes. It must be noted that 7 training icons require only about 5 minutes of training time and this is really a very short time compared to other BCI realizations. But the goal of this study was not to achieve the best accuracy and fastest time, it was to show the performance of different mask types.

Interesting is that three masks (Music, Temp and Move) were controlled with around 75 % accuracy. The three masks have 50, 38 and 13 icons. Normally the amplitude of the P300 potential increases if more icons are used because the likelihood is smaller that the specific icon is highlighted and this results usually in a higher accuracy. Interesting is here that event the Move mask was as good controlled as the other two with only 13 icons. Of special interest is the GoTo mask which appears to be quite similar to all the other masks. The mask had 22 icons and therefore more than the Move mask but achieved only a total accuracy of 26 %. Also the P300 analysis shows that the potential generated by the mask is smaller than for the other masks. The reason for that can only be the layout of the mask itself and this will be investigated in further studies.

However, the experiment yielded 2 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. The BCI system was trained with EEG data of the 7 randomly selected icons and the subject specific information was used for all other commands. 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 control of almost any device with such a BCI system. Especially applications which require reliable decisions are highly supported. Therefore the P300 based BCI system is an optimal tool 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. Humans just think "I want to grasp the glass" and the real command is initiated by this type of BCI implementation.

5 Conclusions

A P300 based BCI system is optimally suited to control smart home applications with high accuracy and high reliability. Such a system can serve as an easily reconfigurable and therefore cheap testing environment for real smart homes for handicapped people.

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