A Hybrid Brain-Computer Interface for Smart Home Control

Günter Edlinger, Clemens Holzner, and Christoph Guger

Guger Technologies OG and g.tec medical engineering GmbH
Herbersteinstrasse 60, A-8020 Graz, Austria
edlinger@gtec.at

Abstract. Brain-computer interfaces (BCI) provide a new communication channel between the human brain and a computer without using any muscle activities. Applications of BCI systems comprise communication, restoration of movements or environmental control. Within this study we propose a combined P300 and steady-state visually evoked potential (SSVEP) based BCI system for controlling finally a smart home environment. Firstly a P300 based BCI system was developed and tested in a virtual smart home environment implementation to work with a high accuracy and a high degree of freedom. Secondly, in order to initiate and stop the operation of the P300 BCI a SSVEP based toggle switch was implemented. Results indicate that a P300 based system is very well suitable for applications with several controllable devices and where a discrete control command is desired. A SSVEP based system is more suitable if a continuous control signal is needed and the number of commands is rather limited. The combination of a SSVEP based BCI as a toggle switch to initiate and stop the P300 selection yielded in all subjects very high reliability and accuracy.

Keywords: Brain-Computer Interface, Smart Home, P300, SSVEP, electro-encephalogram.

1 Introduction

Human-Computer interfaces can use several different signals from the body in order to control external devices which can be based on muscle activity (EMG-Electromyogram), eye movements (EOG-Electrooculogram), respiration or heart rate variability. Recent improvements in terms of usability and reliability in normal subjects as well as handicapped persons allow now the usage of electrical brain activity (EEG-Electroencephalogram) as input signals. EEG-based brain-computer interface (BCI) systems have been realized on various phenomena of the awake brain: (i) slow cortical potential shifts [1] , (ii) the P300 response [2;3], (iii) steady-state visually evoked potentials (SSVEP) [4;5] or (iv) somato-sensory rhythm (SMR) based i.e. motor imagery [4;6].

For the control of a smart home environment evoked potential BCI approaches are the most suitable ones because these approaches allow to select certain target commands out of many different commands to initiate a control. A further big advantage of these approaches is that the user can be trained within a short period of

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time just with a very small sub-set of the possible selections. This means if the smart house has in total 200 control option, the BCI system can be trained on only 5 different icons. This allows the BCI system already to distinguish and classify between the 200 functions with high accuracy and relatively high speed (5-30 seconds per decision).

Another obstacle found in BCI literature is the fact that a certain percentage of the population cannot operate a specific type of BCI due to various reasons. Inter-subject as well as intra-subject variability often leads to a so-called BCI illiteracy [4]. Across the different BCI approaches around 20%-25% of subject are unable to control one type of BCI in a satisfactory way [3]. Therefore, the usage of 'hybrid' BCIs has been introduced into the literature to overcome these problems using the output of somato-sensory rhythm BCI as well as P300 or steady state visually evoked potentials based BCIs enabling subjects to choose between these different approaches for optimal BCI control [7].

A study of Hong et al. recently did a comparison of an N200 and a P300 speller (tested on the same subjects) and found similar accuracy levels for both of them [8]. This gives evidence that a closer look to the N200 component could be promising, at least for some subjects. Hence BCI illiteracy could be overcome or maybe minimized by investigating more thoroughly subject specific preferences. The group of Kansaku reported about the improvement of BCI P300 operation using an appropriate color set for the flashing letters or icons [9]. However, previous studies using the P300 BCI approach for the control of devices within a virtual smart home environment [10] indicate that such an evoked response based BCI can be reliably utilized. Interface masks having different complexity depending upon the capability of the devices can be operated. Another issue in BCI control is to tackle the so called zero class problem [7;11]. A P300 speller for example can be operated successfully from a high percentage of the population with high accuracy and reliability. However, starting and stopping, i.e. switching on and off the BCI operation is still done manually. Both, P300 and SSVEP BCIs were selected for the study setup as recent studies indicate [12] that also severely handicapped people could operate a P300 BCI in a satisfactory way. Allison et al [13] and Zhang et al. [14] showed that only selective attention onto a pattern alone is sufficient for SSVEP based BCI control . The latter paper achieved an overall classification accuracy of 72.6 +/- 16.1% after 3 training days. Therefore also severely disabled people, who are not able to move their eyes, can control an SSVEP-based BCI.

The current study introduces the usage of a hybrid BCI approach for optimizing control comfort of certain interface masks i.e. using (i) the P300 approach for when one selection out of many classes have to be done and (ii) using an SSVEP based toggle switch to start and stop the P300 BCI. As a test bed environment various domotic devices in a smart home environment were controlled.

2 Combined P300 and SSVEP BCI Approach

2.1 P300 Base System

The P300 spelling device is based on a rectangular matrix layout of different characters or icons displayed on a computer screen. A single character or icon is flashed on and off in a random order as shown in Fig. 1A. The underlying phenomenon used to setup a P300 speller is the P300 component of the EEG, which is elicited if an attended and relatively uncommon event occurs. The subject must concentrate on a specific icon he/she wants to select. When the icon flashes on, a P300 component is induced and the maximum in the EEG amplitude is reached typically 300 ms after the flash onset. Such a P300 signal response is more pronounced in the single character speller than in the row/column speller and therefore easier to detect [3].

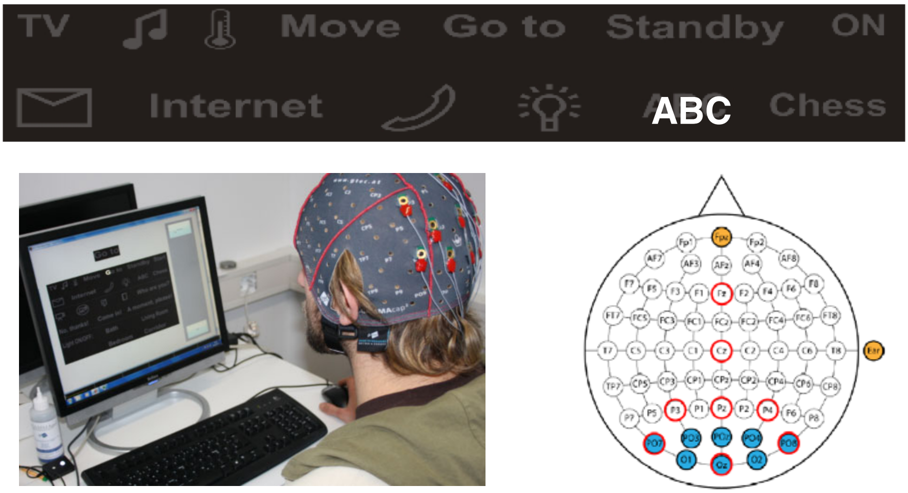

Fig. 1. The upper panel displays an example of the BCI user interface mask with the standby icon ('Standby') and keyboard icon for spelling ('ABC'). The lower left panel displays a subject equipped with an active electrode system (g.GAMMAsys, g.tec medical engineering Gmbh, Austria) operating the SSVEP-P300 interface mask. The lower right panel indicates the used electrode positions. A total of 13 electrode positions are mounted over the parietal and occipital areas according to the international extended 10/20 system.. The red color coded electrodes (Fpz, Cz, P3, Pz, P4, PO7, Oz, PO8) are utilized for P300 operation and the blue color coded positions (PO7, PO3, POz, PO4 PO8, O1, Oz, O2) for SSVEP operation. The ground electrode is positioned at Fpz and the right ear lobe is utilized for the reference electrode.

For BCI system training, EEG data are acquired from the subject while the subject focuses on the appearance of specific letters in the copy spelling mode. In this mode, an arbitrary sequence of icons is presented on the monitor. First, the subject counts whenever the first target icon flashes. Each icon is flashed on for about 100 ms per flash. Then the subject counts whenever the second target flashes until it flashes 15 times, and so on. EEG data are evaluated with respect to the flashing event within a specific interval length, processed and sent to an linear discriminant analyzer (LDA) to separate the target icons from all non targets. This yields a subject specific weight vector WV for the real-time experiments. It is very interesting for this approach that the LDA is trained only on e.g. 5 icons representing 5 classes and not on all possible classes in the mask (details about P300 speller setup can be found in [3]).

2.2 SSVEP Base System

SSVEP based BCI system use flickering lights (LEDs) or flickering symbols on a normal computer screen to visually stimulate the user with a certain flashing frequency between 5 up to 25 Hz. If a light source is flickering with e.g. 14 Hz and the user is looking at it, then an EEG signal with an increased power at the stimulation frequency will be evoked over the occipital areas and can be made visible in the power spectrum of the EEG data (see Fig. 2). The evoked signal power drops down if the stimulation frequency increases. For a fixed stimulation frequency a simple threshold criterion can be used to determine if the user is looking at the light source, otherwise a LDA can be trained with the individual data to find the optimal threshold. If the number of light sources is increased a multi-dimensional control can be realized.

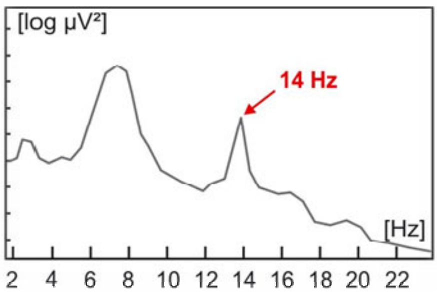

Fig. 2. Power spectrum of the EEG with a peak at the stimulation frequency at 14 Hz. The x axis displays the frequency in Hz and the y axis yields the log power.

2.3 Virtual Reality Smart Home Test Bed Setup

In order to operate the BCI control in the virtual environment several components have been developed. (i) biosignal amplifiers must be able to work in such a noisy environment; (ii) the recordings should ideally be done with a rather small portable device to avoid collisions and irritations within the environment; (iii) the BCI system must be coupled with the VR system for real-time experiments and (iv) a special BCI communication interface must be developed to have enough degrees of freedom available to control the VR system. Fig. 3 illustrates the necessary components in detail. A 3D projector is located next to a projection wall for back projections. The subject can be positioned in front the projection wall to avoid shadows and is equipped with position tracker to capture movements, shutter glasses for 3D effects and the biosignal amplifier including electrodes for EEG recordings. The XVR (eXtreme VR, VRmedia, Pisa, Italy) PC is controlling the projector, the position tracker controller and the shutter glass controller. The biosignal amplifier is transmitting the EEG data to the SSVEP - P300 BCI system which is connected to the XVR PC via UDP connection to exchange control commands.

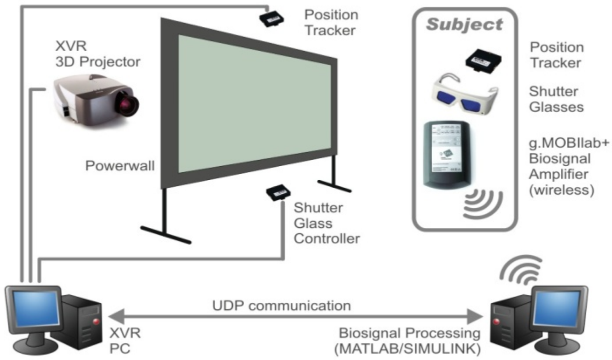

Fig. 3. Scheme of virtual environment setup

The virtual smart home itself consists of different rooms whereby each room is equipped with several different devices that can be controlled: TV, MP3 player, telephone, lights, doors, etc. Therefore, all the different commands were summarized in 7 control masks: a light mask, a music mask, a phone mask, a temperature mask, a TV mask, a move mask and a go to mask. Fig. 4 shows the TV mask and as an example the corresponding XVR image of the living room. The subject can e.g. switch on the TV by selecting the TV symbol. Then, the TV station and the volume can be regulated. For further details see [10]. In such an application, precise timing between the appearance of the symbol on the screen and the signal processing unit is very important. Therefore, the flashing sequence was implemented under Simulink where the real-time BCI processing was also running. Fig. 5 shows a Simulink model processing the EEG data in real-time and combining BCI control to the virtual smart home environment.

Fig. 4. Left panel: TV interface mask. Right panel: Example of the virtual living room displaying domotic devices to be operated like the TV set, music set, room light or chess board.

The signal and processing flow in Fig. 5 starts from the left hand side and progresses to the right hand side. The biosignal amplifier g.USBamp (g.tec, medical engineering GmbH, Austria) is reading 13 EEG channels into the model and is pacing the real-time application. The 'Source Derivation' block splits the channels and sends 8 EEG channels to the 'Signal Processing SmartHome' block for P300 control and another 8 EEG channels to the 'SSVEP Processing' block. For the P300 processing chain data are band-pass filtered and downsampled to 64 Hz and the Signal Processing SmartHome block is performing the feature extraction and classification for the P300 system. The 'Control Flash SmartHome block' controls the icons representing the User Interface. The 'Sockets SmartHome' block send the specific commands to the smart home XVR control server via a UDP connection.

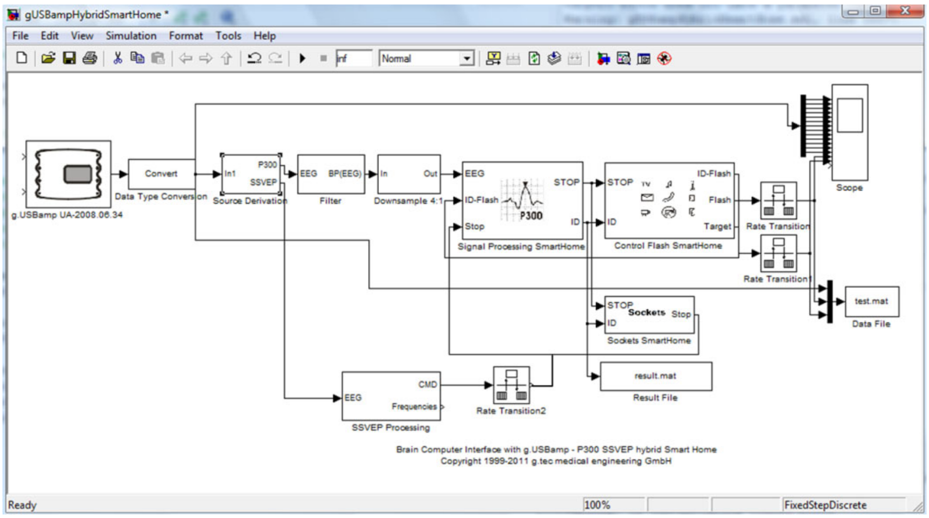

Fig. 5. Simulink real-time processing model of the combined P300 and SSVEP system

The 'SSVEP Processing' processes the EEG channels utilizing the Minimum Energy (ME) algorithm [15]. ME in principal projects artificial signal oscillations at the fundamental stimulation frequencies as well as the 1st and 2nd harmonics onto the orthogonal complement of the EEG-signals. The algorithm further combines the input channels in such a way, that the outcome energy is minimized. The presence of the stimulation stimulus and thus the attention of the user to the flashing light is determined by a test statistics which calculates the ratio between the signal with an estimated SSVEP-response and the signal where no visual stimulus is present. The output of the block is finally used to switch on and off the BCI system.

A total of 3 healthy subjects all right handed males between 25 and 36 years with no contraindication for observing flickering lights operated the combined P300 - SSVEP setup in the virtual smart home environment. To be able to measure the SSVEP signal electrodes must be mounted over parietal and occipital sites of the cortex as shown in Fig. 1 lower panel. The SSVEP method requires 8 EEG electrodes to show a high classification accuracy. The P300 uses 8 EEG electrodes over frontal, central, occipital and parietal sites and has 3 electrodes in common with the SSVEP principle. Therefore in total 13 electrodes will be investigated. The active electrode system g.GAMMAsys was mounted according to the electrode position given in Fig. 1 lower panel and EEG data were sampled at 256 Hz using g.USBamp.

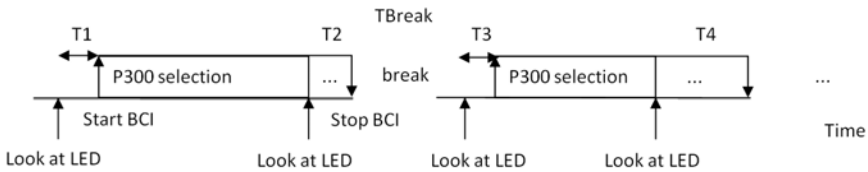

Fig. 6. Experimental paradigm and timing for the SSVEP - P300 experiment

A bright LED light source was connected to a special programmable stimulation device. The stimulation frequency was set via USB connection and a Simulink interface to 14 Hz. Subjects had to follow a certain paradigm in order to test the reliability and performance of the system (see Fig. 6). In order to start the operation of the BCI subjects were instructed to concentrate and look to the 14 Hz flashing light which is used here as a ON/OFF toggle button. After the 14Hz activity has been detected by the ME algorithm from the EEG (time T1), subjects had to select 5 predetermined commands from the P300 speller mask. Icons were flashed on in this case for 15 times so the P300 operation time has been fixed. Then the subjects had to operate the SSVEP toggle button to switch off the speller (switching off time T2). Before the next trial was started subjects had to wait for approximately one minute (TBreak) in order to determine false positive operations of the toggle button. An operator instructed the subjects verbally to continue the BCI operation by looking again at the flashing light to switch on the speller again. This procedure was repeated for 10 rounds of SSVEP - P300 operation.

3 Results and Discussion

Table 1 displays the results for the SSVEP controlled toggle switch and P300 accuracy for 3 subjects. T SSVEP on7off yields the mean time needed for switching on and off the BCI operation. All subjects needed about 4.5-5 seconds to switch on the BCI toggle button and about 5.8 to 7.9 seconds to switch it off again. Spelling accuracies were 100% for the 5 target icons. In the break in between the 10 spelling experiments only S3 displayed one false positive result.

BCI enabled control and communication is a new skill a subject has to learn. In an initial adaptation phase the BCI system is trained to the specific subjects brain activity. In addition the subjects have to get used and adapt to the BCI system as well. The time needed for a subject to adapt to the system is by far shorter in exogenous BCIs like P300 and SSVEP approaches [3;4]. Such BCI systems yield higher accuracies in a higher number of subjects and give therefore for control purposes more reliable results. The current study introduces a combined thus sequential usage of 2 types of BCI concepts.

Such an approach has the advantage that users might benefit from a more optimal performance of the overall system as subparts of the system are based on the most suitable control approaches. Pfurtscheller et al [7] introduced a SMR based BCI as brain switch. However, it is know from the literature that a reliable control of SMR

Table 1. Mean switch on/off time, P300 accuracies and number of correct operation of the toggle button

	T SSVEP On/Off [s]		P300 Accuracy [%]	Number of correct operation of toggle switch	
	On	Off		TP	FP
S1	4,6	7,8	100	10	0
	Mean 6,2				
S2	4,48	5,8	100	10	0
	Mean 5,14				
S3	5,05	7,92	100	11	1
	Mean 4,68				

activity needs a long training period [3]. Furthermore in a high percentage of the population such an approach could not be used. In contrast to SMR BCIs evoked potential based BCIs showed a better overall performance and reliability. However, focusing a very long time to flickering light sources, either flashing at distinct frequencies for SSVEP approach or flashing randomly for the P300 approach might distract people from their daily activities or simply annoy users after some time. Therefore the SSVEP approach might be utilized to operate a simple on/off toggle button in a very reliable way. Hence the BCI operation can be started and stopped arbitrarily by the user without the need of an operator intervention. In the current experiments only one false positive toggle switch event within the total of 30 min forced breaks was observed for SSVEP - P300 BCI. The operation of a speller like interface, i.e. the operation and selection of target commands out of many commands works in a very reliable way based on the P300 approach. In Guger et al. the spelling performance of a total of 100 subjects was investigated and more than 90% of the subjects could operate the P300 speller with 100% accuracy [3]. Edlinger et al. reported on the usage of the P300 BCI in the smart home environment [10]. There the authors concluded that the performance of the P300 control is comparable to the classical 6x6 speller. However, the authors also state that designing the interface masks in a more proper way can improve the usability and success rate in BCI. Moreover for simple control masks with less symbols to select like moving e.g. a device in one out of four directions the SSVEP based control might be more reliable and faster. Results of the current study suggest that a combined or hybrid BCI approach such as using the P300 BCI approach for a many class selection task and using the SSVEP especially as a toggle switch to initiate and stop BCI operation is promising. Furthermore the SSVEP interface can enhanced in a straightforward manner by adding other control flickering lights to improve the performance for e.g. a four class selection task within the smart home environment.

4 Outlook

Based on the experiments in the virtual smart home, the BCI system is currently further advanced to be used within a real smart home developed for independent living for handicapped people. Here the BCI system is embedded in a middleware platform that allows controlling multiple domotic devices with the BCI system.

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