An Augmented-Reality Based Brain-Computer Interface for Robot Control

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Abstract. In this study we demonstrate how the combination of Augmented-Reality (AR) techniques and an asynchronous P300-based Brain-Computer Interface (BCI) can be used to control a robotic actuator by thought. We show results of an experimental study which required the users to move several objects placed on a desk by concentrating on a specific object. Competitive communication speed of up to 5.9 correct symbols per minute at a 100% accuracy level could be achieved for one subject using an asynchronous paradigm which enables the user to start communicating a command at an arbitrary time and thus mitigating the drawbacks of the standard cue based P300 protcols.

Keywords: P300 BCI asynchronous speller augmented-reality robot.

1 Introduction

Recent years have brought up a tremendous growth of contributions to the field of brain-computer interfaces (BCI). In general, BCI allow to infer mental commands of the user by measuring their brain potentials with *electroencephalography (EEG)*. Such a system enables a direct communication between a computer and the user without using any motor function as it is required for speaking, eye-tracking or using a mouse or keyboard. Nowadays the application of BCIs, once intended for people with severe motor disabilities , spans the full range of medical to entertainment scenarios.

Two popular strategies are employed in modern BCIs which control artificial actuators. As reviewed by [7], control strategies can be distinguished by *Process Control* and *Goal Selection* (see figure 1). Thereby, process control strategies aim at direct control of the available motors or muscles which result in an action while goal selection approaches focus on recognizing the intent of a user. The intent serves as input for an execution unit which translates it to a sequence of motor actions. Obviously, the goal selection approach does not require the user to achieve full control over the output device via brain signals. A rather simple *goal selection* scheme would be sufficient which requires only a one dimensional selection of a target symbol corresponding to the desired action while the process control approach would require the user to be able to control at least 3 DOF

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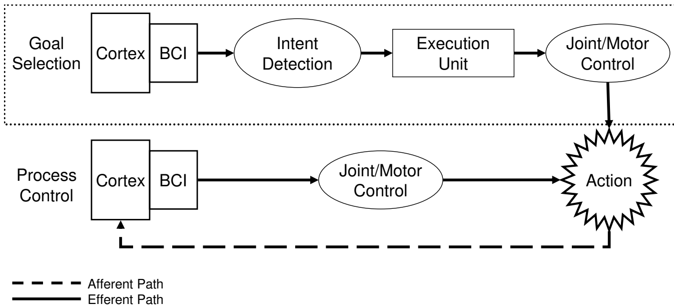

Fig. 1. Depicted are the two main approaches when using BCIs to control a robotic device. Process control establishes a closed feedback-loop between action and the brain and offer full control over the robot. Goal selection approaches are easy to use since actual motor control is delegated to autonomous subsystems.

to navigate freely in space. With goal selection approaches, actual control is delegated to system subcomponents (e.g. robot controller) which do not require control via higher cognitive functions. This reflects the normal output pathways of the brain and its underlying systems for motor control. Thus, it can be stated that goal selection approaches are currently the most natural way to control robotic output devices by brain signals. A popular type of goal-selection BCIs is the P300-Speller paradigm [2] which presents visual stimuli in rapid succession and random order. The subjects are required to attend to a specific stimulus and mentally count whenever the focused stimulus appears. The appearance rate of this *relevant stimulus* is low compared to the other *background stimuli*. Whenever the relevant stimulus appears, a positive deflection in the EEG occurring at 300ms after stimulus onset can be observed. This component, called P300, is utilized by P300 BCIs to predict the user's selection. A drawback of most goal-selection systems (primarily P300-based BCIs) is the assumption that the user is trying to communicate with the BCI at all times. While this assumption makes it possible to easily implement the selection method via visual or auditive cues that signal the start of a selection round (i.e. trial), it is an unreasonable constraint for a practical application. Even though P300-based BCI require external stimulation, and thus are reliant on cues to some degree, it is possible to omit the trial-based nature of these paradigms. A system which is able to continuously present stimuli and detect whether a user is currently trying to communicate with the system is considered an *asynchronous BCI*. Operating in an asynchronous mode is vital for any practical application involving control of robotic actuators since it allows to intervene or start communicating with the system at any time.

Recent research has brought up new methods for stimulus dependent BCIs to achieve this kind of behavior. In [6] the control of a wheelchair is realized by using buttons on a screen as selection targets for a P300 BCI. Each button is associated with a preprogrammed path the wheelchair should take. Their system features

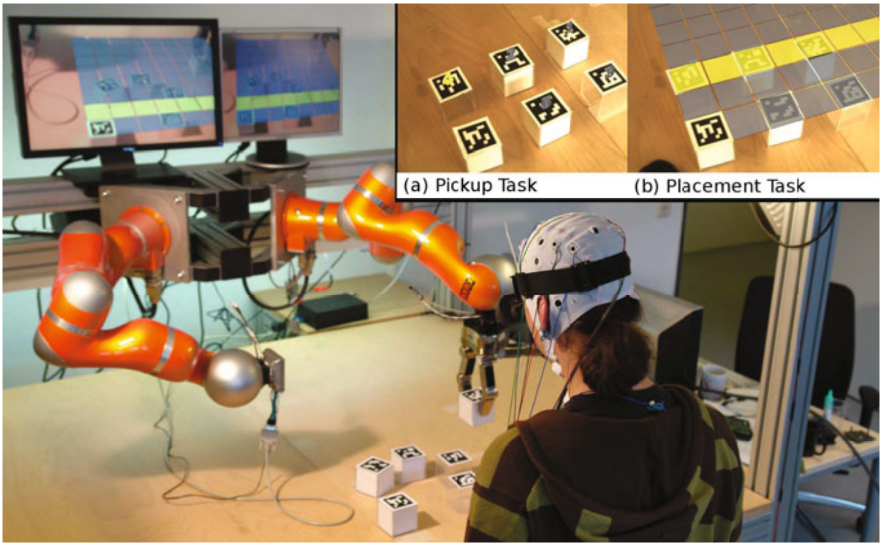

Fig. 2. Scene setup with robot arm and marker objects. (a) Scene as viewed through the HMD during the *pickup* task. (b) Scene during the *placement* task.

an asynchronous protocol that allows the subject to issue commands at any time. Similar work related to the detection of *no-control* states has been presented by [8]. Instead of exploiting the distribution of class scores, they proposed a method which computes a probabilistic model of EEG data during no-control periods.

In this paper we present an asynchronous P300 BCI designed to grasp and place arbitrary objects using a robot arm with an attached gripper. A method to dynamically adapt the stimulus content which represents the physical scene in front of the subject using augmented-reality techniques will be described. Further, an extended version of the asynchronous protocol as presented by [6] will be evaluated. A preliminary study with 4 healthy subjects was conducted to test the usability of the system.

2 Augmented-Reality BCI Design

The BCI setup consists of a Kuka robot arm with an attached Schunk SDH-1 gripper, a stereoscopic video see-through head-mounted display (HMD) with two integrated firewire cameras and a g.tec gUSBAmp 16 channel EEG amplifier. Five plastic cubes with attached markers on the upper side were placed on a desk. When the scene is observed through the HMD, 3D models of numbers are augmented on top of these cubes as seen in figure 2. The markers are special 2D bar code images which code a unique number. These bar codes are recognized by the vision component of the BCI system. Interaction with the scene is a two-step process consisting of an *object pickup* and and *object placement* task.

2.1 Experimental Protocol

The selection of an object is achieved by flashing up all numbers one-by-one in random order (Fig. 2 (a)) while the user mentally counts whenever the desired object flashes. At the beginning of each flash a short EEG time window (epoch) of 700ms is extracted and passed to the classification method. An object is selected when the classification method reports sufficient confidence in the current prediction. On a successful classification, the 3D coordinates and orientation of the object are extracted using the available methods of ARToolkit [4]. Since the extracted coordinates are relative to the camera position but are required to conform with the robots coordinate frame, a special reference marker with known coordinates in the robot frame is used to calculate the objects position relative to the reference marker. This step is necessary since the camera position (i.e. the head of the user) is not tracked. The extracted coordinates are sent to the robot backend with the instruction to grasp the object. Placing an object works in a similar way. After an object has been grasped, the reference marker serves as the origin for a semi-transparent 8×8 chessboard model as shown in Fig. 2 (b). Each cell of the board corresponds to a spatial location on the desk. Selecting a location is done in the same way as in the well known P300-Speller paradigm [2] by flashing up rows and columns in random order. The intersection of the row and column with the highest classification score will correspond to the selected grid cell.

3 Methods

The classification of epochs containing P300 event-related potentials requires an initial training step in which EEG data of the user is collected. During the training phase, the system starts in object selection mode and marks a random cube by highlighting its associated stimulus in green for 3 seconds. The user is advised to mentally count whenever this stimulus is flashed. The BCI then starts to flash the stimuli in random order in a 200ms interval. After all stimuli have been flashed 5 times, the BCI switches to grid mode and repeats the procedure analogously. The flashing of all rows and columns are flashed in random order once is repeated 5 times resulting in 80 stimulations per trial in this mode.

3.1 Data Acquisition

EEG data from the position *10-20 locations* [3] O1, O2, Pz, P3, P4, Cz, C3, C4, FCz, Fz, F3 and F4 were collected at 256Hz sampling rate using a 16-channel gUSBAmp EEG amplifier with reference and ground electrodes attached to the left and right mastoids. The derivation method was set to common reference which measures the potential differences between the active and the reference electrode. During the training phase, data of 20 stimulus presentation rounds (trials) for each task (*pickup/placement*) were collected. All data were highpass filtered to at 1Hz and subsequently downsampled by a factor of 16. No effort has been made to remove eye blink and muscle artifacts from the training set.

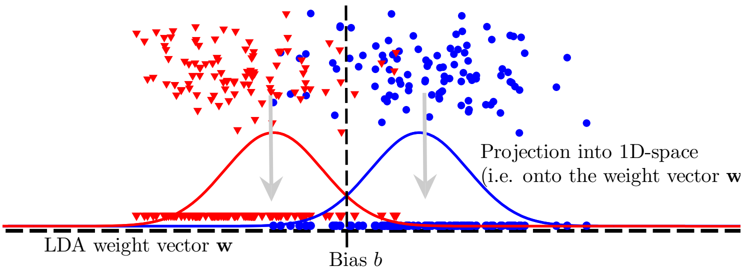

Fig. 3. Classification score distribution for P300 and non-P300 class

3.2 P300 Classification

Using the data obtained during the training phase, a two-class dataset containing both P300 (P^+) and non-P300 (P^-) time windows of 700ms (epochs) was extracted. The set was balanced to contain an equal number of observation for both classes. Each epoch was concatenated channel wise to form a single epoch vector $\mathbf{x}$. A *Fisher Linear Discriminant* classifier with regularized covariance matrices was trained on these data by computing

$$\mathbf{w} = \mathbf{S}_W^{-1}(\mu_+ - \mu_-) \tag{1}$$

with $\mathbf{S}_w$ being the regularized *within scatter matrix* which is defined as the sum of sample covariance matrices of both classes $\mathbf{S}_+ + \mathbf{S}_-$. The mean vectors of the P300 class are represented by μ_+ while the non-P300 means are represented by μ_-. A classification score is obtained by projecting an epoch vector $\mathbf{x}$ onto $\mathbf{w}$ resulting in a scalar value. Positive values correspond to a P^+ class assignment while negative values are associated with the P^- class.

3.3 Asynchronous Control for P300 BCIs

To mitigate the drawbacks of the trial based nature of classical P300 BCIs, we developed a novel flexible method similar to [6] extending our previous work [5]. Classical P300 BCIs use a fixed number of stimulus presentation round to acquire multiple EEG segments for each stimulus (epochs) which are subsequently averaged to improve the signal-to-noise ratio for improved classification accuracy. Using this method, a cue (marking the start of a new trial) is required that instructs the user to start focusing on the symbol she wants to select. In contrast to the classical approach of using dedicated time intervals during which data is collected for a classification, we are continuously presenting stimuli and collecting EEG epochs for each stimulus. While the first approach can be considered as a *batch method* as it needs to acquire multiple EEG epochs and further assumes that the subject is focused on the BCI, our new method is an *online method* that successively adds EEG epochs and dynamically decides when to output a classification. In that sense, our new method has two major advantages over the classical approach. Given a function P that measures the confidence of a classification result based on n epochs, a trial can be ended whenever P exceeds a certain threshold. As shown in [5] this can significantly reduce the number of stimulus presentations. As a second advantage, our method does not rely on the assumption that the subject is trying to communicate with the BCI at all time and thus can be considered as an asynchronous BCI. We will show that both problems of detecting *no-control/intentional-control* states of the subject and detection of the optimal number of subtrials are in fact closely related problems which can be solved by computing a single metric based distribution of classification scores.

Depicted in figure 3 is a simplified sketch where the points represent the EEG data epochs which are being projected onto the weight vector $\mathbf{w}$. These scores will be interpreted as features and the gaussian PDF properties μ and σ^2 for both classes in the feature space are estimated from the training set. In its simplest form, the method works by iteratively adding scores for each corresponding target i to an observation vector $\mathbf{x}_i$. A subsequent two-sided z-test is conducted with the $H0$ hypothesis that the observation mean $\overline{\mathbf{x}_i}$ is equal to the P300 class mean μ_+. A sequence of classification scores is considered *reliable* whenever the z-test can not reject H0 at a given significance level. Using this approach, the problem of finding the optimal number of stimulus presentations is solved since with increasing subtrials $\overline{\mathbf{x}}_i$ will converge towards μ_+ if i is the attended symbol and towards μ_- if i does not correspond to an attended symbol. At the same time, the second problem of detecting *no-control* states is solved. When the subject is not focusing on the BCI, it is unlikely that mean scores will converge towards μ_+ and thus all targets will be classified as P^-.

More formally, the method utilizes the standardized z-statistic

$$z(\mathbf{x}, \mu, \sigma^2) = \frac{\overline{\mathbf{x}} - \mu}{\sigma^2/\sqrt{n}} \tag{2}$$

to estimate the observation mean value's deviation from the true mean μ. A decision function that determines the end of a trial can be formulated as

$$\mathcal{D}(\mathbf{x}_i, \alpha, \mu, \sigma^2) = P(z(\mathbf{x}_i, \mu, \sigma^2) \leq z_{p=\alpha} | H_0) < \alpha \tag{3}$$

with z_p being the quantile function which can be derived by inversion of the standard normal cumulative density function. This formulation allows to define a *confidence level* α which can be used to tune the BCI for higher speed or higher accuracy. With increasing α, the acceptance interval around the P^+ mean is getting smaller which in turn mean that fewer scores will be accepted for the P^+ class assignment. With very high confidence levels it is even possible that no classification occurs at all. Thus, the general aim is to minimize false positives[1] while keeping the acceptance rate at a reasonable level.

[1] i.e. Labeling a sequence of classification score for one symbol as P300 epoch when it is in fact belonging to the non-P300 class.

4 Experimental Results

An experiment was conducted with 4 mixed male and female subjects with the aim to evaluate the overall usability of the system and the feasibility of the asynchronous protocol. The task for the subject was to move objects placed in front of them to a different location on the table. Both, the object and the target location were chosen by the subject. Whenever the robot picked up or placed an object, the subject was asked to report on the correctness of the robots action. The experiment ended when the subject successfully moved 10 objects to different locations which required 20 selection commands (i.e. 10 for *pickup* and 10 for the *placement* task). The task performance was measured by calculating the communication rate in correct symbols per minute, as well as the overall accuracy. To evaluate the feasibility of the asynchronous protocol, the subject's focus had to be distracted from the BCI stimulus presentation. For this reason, they were asked to fill out a short questionnaire and answer to question of the experiment supervisor after the experiment ended. During that time the BCI was still running and ready to receive commands. Further, to evaluate how long the system takes to recognize that the subject is now actively communicating with the system, one more object relocation had to be carried out. Table 1 summarizes the number of wrongly conducted actions per minute during questionnaire period as well as the time it took the system to recognize a voluntary selection command of the user (i.e. *time to active (TTA)*).

Table 1. BCI performance achieved in the study. The measures accuracy (Acc.), correct symbols per minute (Sym./min), actions per minute during the *no-control* period and *time to active* (TTA) are shown.

	Pickup Task		**Placement Task**		**No-Control Task**	
Subject	Acc.	Sym./min	Acc.	Sym./min	Act./min	TTA
S1	80%	3.3 (2:20)	70%	1.1 (6:30)	0.4	12s
S2	90%	2.3 (2:50)	70%	1.4 (5:00)	0.6	18s
S3	100%	5.9 (1:40)	90%	1.7 (5:50)	0.2	8s
S4	80%	2.3 (3:40)	60%	0.7 (8:20)	0.8	10s
Mean	87.5%	3.45	72.5%	1.23	0.5	12

5 Discussion

For the *pickup* task, promising accuracies of 80% up to 100% across all subjects could be achieved. The communication speed is roughly between 2 and 3 symbols/min except for subject 3 who performed exceptionally well compared to the other users. These values however dropped significantly during the *placement* task. While the performance loss in terms of communcation speed was expected since this task contains 64 stimuli in contrast to the 5 stimuli of the *pickup* task, the accuracy loss is remarkable. We explain this loss of accuracy with the fact that all subjects noted on the questionnaire that it is difficult to keep focused on a specific grid cell due to their equal appearance. All of them remarked that during the training and online phase their attention slipped to adjacent cells from time to time. One subject also noted that the cell he was focusing seemed to visually fade when he was focusing it for a sustained time. Contrary, none of the users had problems to stay focused during the *pickup* task which used unique 3D models of numbers as stimuli. We assume that this issue could be related to the rather poor performance of subject 4 during the placement task. The evaluation of the asynchronous protocol shows an average misclassification rate of 0.5 symbols per minute. For this experiment, the α value for the decision function (Eq. 3) was set to 0.2 which seemed to be a reasonable tradeoff for speed and accuracy. On average, our method achieves a false positive rate (FPR) of 0.5 symbols per minute which is comparable to the work of [8] with an FPR of 0.71. Similar to Zhang et al. the accuracy of the system can be optimized at the cost of communication speed. The overall performance of the system is sufficient for practical use (e.g. for motion impaired people). The current limitation of marker based pose estimation can also be replaced by a more sophisticated method using natural features [1]. Practical tasks could consist of picking up a variety of objects like telephones, books or using a TV remote control. In the near future, this method could also be extended to aid in *hands-busy tasks* for healthy subjects as mentioned in [9].

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