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Interaction with Virtual and Augmented Reality Environments using Non-Invasive Brain-Computer Interfacing

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***Abstract*—In electroencephalogram (EEG) based brain-computer interfaces (BCI) systems, evoked potentials provide a relatively accurate way of selecting between large numbers of classes. However, they rely on external stimuli. Mental imagery (e.g. motor imagery), on the other hand, does not require external stimulation and allows real-time control but the detection of induced EEG patterns can be error-prone. In this paper we propose a scalable, user-adaptive BCI that combines the advantages of imagery and evoked potentials. Users utilize imagery to teach the BCI new commands, which are then made available for selection using evoked potentials (e.g., the P300). We present preliminary results illustrating the proposed approach.**

Keywords: Electroencephalogram, Brain-Computer Interface, Virtual Reality, Augmented Reality, Bionics.

I. Introduction

BRAIN-Computer Interface (BCI) technologies provide a novel way for humans to communicate and interact with the environment. BCIs are not dependent on actual movements; instead, BCIs process the user's intent directly and translate brain activity into control commands for devices [1]. For the translations BCIs rely on digital signal processing, and on pattern recognition and machine learning. Electroencephalographic (EEG) signals recorded from the scalp are the most common source for non-invasive BCIs in humans.

Virtual Reality (VR) and Augmented Reality (AR) can be efficient and powerful tools for enhancing and studying BCI technology. In immersive Virtual Environments (VEs), BCI users tend to make fewer errors, find BCIs easier to learn and use, and report that they enjoy using the BCI more (e.g. [2, 3]).

In this paper, we propose a novel approach to building scalable, user-adaptive BCIs that originate from two different types of BCIs we have demonstrated previously. The first, a self-paced mental imagery BCI, was designed to e.g. replace manually operated joysticks for navigating through VEs [3, 4]. The second P300-based BCI was designed for sending high-level commands to a semi-autonomous humanoid robot for physical interaction with real objects in AR [5].

In the following we review the imagery and P300-based BCIs, and describe the basic principles and current status of the scalable, user-adaptive hierarchical learning framework.

II. Methods

A. Replacing Manually Operated Joysticks

BCIs that allow the user to voluntarily modulate brain activity whenever the user wishes to issue commands are called self-paced. One class of mental tasks used to encode commands is motor imagery (MI). MI is known to induce distinguishable changes in oscillatory EEG activity (known as event-related (de)synchronization ERD/ERS events [6]) over sensorimotor areas. In [4] we described such a self-paced BCI based on sensorimotor rhythms that can discriminate between three different motor imagery classes from ongoing EEG. The BCI used this output to navigate in a VE. In particular, users could issue navigation commands *rotate left, rotate right* and *move forward* by imagining left hand, right hand, and foot (or tongue) movements, respectively. The user's task in the VE was to navigate and find coins that were scattered randomly at different locations in the environment. By continuously imagining a specific mental task, switching between imagery, or not performing motor imagery at all, navigation commands were decoded and sent to the VE.

Three users took part in the navigation study. After about five hours of feedback training (see [4] for more details) satisfactory self-paced navigation became possible. The classification accuracy between the three types of imagery was approx. 80%, with about 17% false positive detection whenever no navigation command was required. The time lag from motor imagery onset to correct classification of induced patterns was around 2.0s. These results might be lower than others reported in the literature due to the fact that to increase the usability of the BCI, the number of bipolar EEG channels was limited to three. Fig.1(a-b) show the VE and example trajectories.

B. Issuing High-Level Commands

To reach their goal in the above study, users were required to continuously perform mental imagery. Such a control

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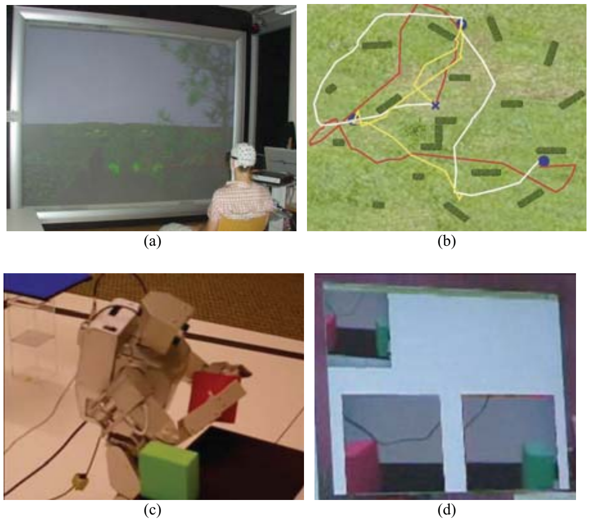

Figure. 1 (a) VE presented on stereoscopic projection wall. (b) Map of the VE consisting of trees and hedges with three example trajectories (white, yellow and red line). The “x” marks the starting position. “o” marks the position of the coins subjects had the task to collect. (c) HOAP2 humanoid robot executing selected high-level command from user. (d) Live feedback images from the robot’s camera for P300 based BCI. The smaller image in the upper left corner of the computer screen is the live feed from the robots camera. The larger images in the lower part of the screen show the segmented objects, here a red and a green cube. User attends to image of desired object while borders are randomly flashed (red square). (Images (c) and (d) from [5], courtesy of R. Chalodhorn).

protocol, however, might be too tedious and strenuous for users. For a number of tasks, selecting high-level commands representing the user’s goal would be more desirable. Intelligent artificial devices (e.g. a motorized wheelchair with path planning and obstacle avoidance capabilities) can then be instructed to autonomously perform the task. Whenever the executing device needs additional instructions for task completion, the user can be asked for assistance.

In [5] we used the P300 visual evoked potential to select high-level commands, which are executed semi-autonomously by a humanoid helper robot (Fujitsu HOAP). The robot has the ability to autonomously move and pick-up/release objects (Fig.1(c)). The robot also possesses some computer vision capabilities, such as being able to segment objects on a table and use vision to navigate to a destination. The user receives a live feed from the robot’s cameras, thereby immersing the user in the robot’s environment and allowing the user to select actions based on the objects in the image. The BCI was designed to command the robot to navigate to a specific (known) location, transmit images of objects the robot sees at that location, allow the user to select an object for pick-up, and finally, command the robot to bring the object to the user or transport it to a different location.

EEG signals were used to select the two main types of commands for the robot: which object to pick among the ones whose images were transmitted by the robot, and which location to choose as the destination from among a set of known locations. The images of the possible choices (objects or destination locations) were scaled and arranged as a grid on the computer screen of the user. Fig.1(d) illustrates the case of two objects, one red and one green. According to the oddball paradigm used to evoke the P300 response, the user focuses his or her attention on the image of choice while the border of a randomly selected image is flashed every 250 ms. When the flash occurs on the attended object, a P300 can be expected; this response is then detected by the BCI and used to infer the user’s choice.

The results, based on nine able-bodied subjects, show that an accuracy of 95% can be achieved for discriminating between four objects. With the implemented rate of 4 flashes per second, the selection of one out of four options takes 5 sec. This accuracy can already be achieved on-line after a 10-minute data collection and calibration procedure.

C. *Towards Hierarchical BCIs*

We are now developing a new generation of scalable, user-adaptive BCIs that combine the advantages of imagery and evoked potentials. Users utilize imagery to teach the BCI new commands, which are then made available for selection using evoked potentials (e.g., the P300). This leads to a *hierarchical BCI* wherein lower-level actions are first learned and later semi-autonomously executed using a higher-level command, thereby improving accuracy and freeing the user from having to engage in tedious moment-by-moment control. Our goal is to explore the efficacy of such a system in the context of controlling the humanoid robot where new lower level behaviors are learned via imagery and invoked later as higher-level commands via P300.

To investigate the feasibility of such an approach, we performed a first set of EEG-based BCI experiments that intermixed motor imagery and P300 control tasks. Preliminary results from the on-line simulation study (offline analysis), in agreement with other studies on hybrid BCIs [7], suggest that users can switch between the modalities of motor imagery and evoked potentials, and achieve reasonably high accuracies in each case [8].

Our current experiments are focused on investigating whether users can maneuver the robot using imagery (Fig.2) and later invoke these user-taught behaviors directly through P300-based commands. In these experiments, the user attempts to create, on the fly, a new command such as “Go to kitchen” by first navigating the humanoid to the desired location using motor imagery for a few trials. The BCI then uses these trajectories collected from the robot’s on-board sensors during navigation to build a navigational model using a radial basis function (RBF) neural network. On a subsequent run, when the robot is commanded to navigate autonomously to the

Figure 2. Imagery-based control of a humanoid robot.

kitchen based only on a higher level P300-based command, the navigational model autonomously controls the robot by mapping incoming robotic sensor data to appropriate navigational actions until the robot reaches the kitchen. We are currently testing this paradigm in a simulated environment (Fig. 3). Fig. 4 shows some preliminary results illustrating how a small set of user trajectories (simulated in this case; shown in red) allows the system to learn a navigational model and later autonomously navigate to a desired goal location.

III. Discussion

Mental imagery induces changes in oscillatory EEG components without relying on external sensory stimulation, and enables self-paced BCI operation; the detection of such induced patterns, however, is error-prone compared to detecting patterns that are evoked by external stimuli such as the P300. Our approach leverages the benefits of the two paradigms using a hierarchical BCI system that adapts to the user.

The presented applications are only examples of how VR and AR can be integrated with BCI technology. The VE in the imagery-based BCI navigation application can easily be replaced with more complex environments such as museums, exhibitions or even entire cities (e.g. [9]). This would enable, for example, physically impaired or paralyzed BCI users to enjoy cultural experiences from home. Emerging computer graphics tools could allow quick and automatic generation of stereoscopic 3D models from conventional 2D pictures [10].

Artificial devices that are able to automatically detect task-related objects and context-sensitive information, and to merge the results with the real world, such as the humanoid assistive robot we used in our study, are useful tools to reduce the number of BCI-based selections. Non-stationarity and inherent variability of EEG signals are still major problems for the detection and discrimination of brain activity patterns. Minimizing the information

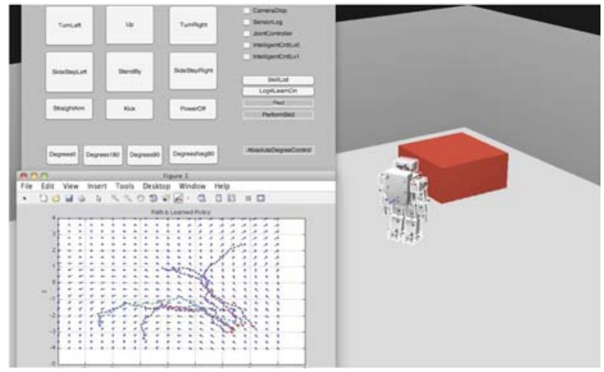

Figure 3. VR simulation of the robot learning a new navigation task. The screenshot shows the simulated HOAP2 humanoid robot executing a high-level command, i.e., the robot automatically moves from the starting position in the VR to the red target. In the upper left corner the graphical user interface for controlling the robot is depicted. Each button represents a command that is available for P300 selection. To evaluate the performance of the navigational model a joystick can be used to control the robot. The window in the lower left corner shows trajectories recorded during user navigation (training samples) and autonomous robot navigation.

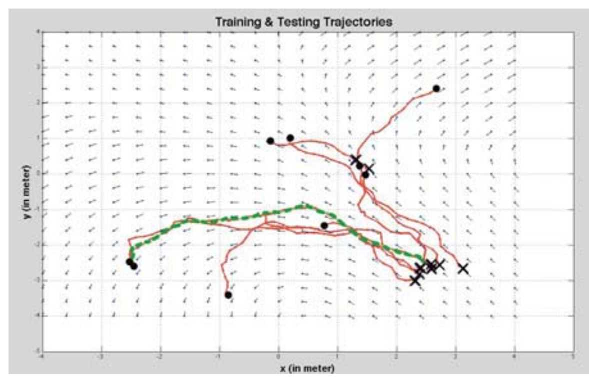

Figure. 4. Representation of the navigational model. The x-axis and y-axis represent x-axis and y-axis of a top-down map of the simulated environment. The red lines are simulated user trajectories generated to test the learning algorithm. The black circles are starting locations and the black crosses are ending locations of the navigation task. These trajectories were used to train the radial basis function (RBF) neural network. The dashed green line is a trajectory generated by the network to autonomously guide the simulated robot. The small arrows indicate the vector field learned by the RBF network based on the red trajectories.

transfer while maximizing the task performance might be one way towards more practical applications.

The combination of mental imagery and evoked potentials allows the development of new paradigms such as the hierarchical user-adaptive scalable learning framework proposed in this paper. The BCI user can not only customize their BCI, but also train connected artificial devices and teach them new behaviors and skills that combine lower-level primitives. In the proposed approach, the best performance is achieved only when the human, the BCI, and the controlled device (the robot) co-adapt in a mutually beneficial manner. Such co-adaptation is a topic of particular importance to the BCI community. As a first step we are investigating this problem within the context of navigation but the goal is to develop models and learning algorithms that can generalize to other tasks as well.

We believe the use of VR and AR in combination with hierarchical BCIs and models of learning may help increase BCI usability, and reveal novel ways in which BCIs can enhance human communication and interaction with physical and virtual worlds.

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