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A hybrid brain interface for a humanoid robot assistant

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Abstract— **We present an advanced approach towards a semi-autonomous, robotic personal assistant for handicapped people. We developed a multi-functional hybrid brain-robot interface that provides a communication channel between humans and a state-of-the-art humanoid robot, *Honda's Humanoid Research Robot*. Using cortical signals, recorded, processed and translated by an EEG-based brain-machine interface (BMI), human-robot interaction functions independently of users' motor control deficits. By exploiting two distinct cortical activity patterns, P300 and event-related desynchronization (ERD), the interface provides different dimensions for robot control. An empirical study demonstrated the functionality of the BMI guided humanoid robot. All participants could successfully control the robot that accomplished a shopping task.**

I. INTRODUCTION

PEOPLE with motor control deficits often need assistance to accomplish every-day tasks. Depending on the kind and degree of impairment, different types of assistive technology are required: for instance, a wheelchair for moving around or a special interface to assist communication. Recently, the advances in the robotics field have led to constantly growing abilities of robots. They can now act autonomously and adapt to new, changing situations. This makes robots a promising platform for assistive technologies. Although one could think of a robotic assistant as a fully autonomous system, humans usually prefer to retain a certain degree of (eventually) optional control over the technical system [1]. To implement additional control channels for an autonomous technical system, one or more suitable input modalities need to be identified. This becomes increasingly difficult the more severe the motor impairment of a patient is because almost all possible input channels require at least some basic motor action (i.e. manual input, speech). We propose to use purely cortical signals - recorded, processed and translated by an EEG-based brain-machine interface (BMI). Such a BMI provides an input channel that functions independently of the severeness of the person's motor impairment and can be used to control an otherwise autonomous humanoid robot.

State detection for a brain-robot interface The assessment of cortical signals by the non-invasive EEG is restricted to the detection of specific states. In the context of robot control such states are usually cortical correlates of movements which indicate that a particular limb (e.g. the left hand) is moving. In this example, the detected state is "left hand is moving". Direct process parameters (e.g., joint angles, velocity, direction) cannot be extracted from EEG recordings. The extraction of motor-related states is feasible during executed, and more important, purely imagined movements and therefore essential for people with motor control deficits.

While, as stated above, invasive interfaces are suited to control actions on joint level, for current state-of-the-art robots the direct access to individual degrees-of-freedom (DOFs) by a human controlled interface is not necessary. At this point it is important to distinguish between two different control strategies: a process-directed and a target-directed strategy [2]. A *process-directed* strategy aims at controlling as many parameters of a process as possible. A *target-directed* strategy defines only targets, that is, discrete points or states of an eventually continuous process. Then, only state changes from one target to another are triggered, while all necessary intermediate steps or actions run in an autonomous manner.

II. THE HYBRID BMI SYSTEM

We have developed an EEG-based, hybrid BMI with a highly modular structure to account for the needs of brain-robot interfaces, in particular to allow for easily interfacing to different (humanoid and other) robots. In the presented study, we use *Honda's Humanoid Research Robot*. Our BMI system is hybrid in the sense that, in contrast to most other current BMIs, it exploits two distinct cortical activity patterns to increase the number of control dimensions provided by the interface.

More specifically, the incoming raw data stream is constantly scanned for both patterns. This is achieved by initially processing the data in two parallel classification pipelines, each optimized to detect the particular pattern. Subsequently, in a second step, a pattern selection algorithm fuses the outputs from the pipelines and decides on the final system output, which may be a real-valued confidence or a discrete class label. We will refer to the whole processing procedure as *state detection*, and to the final system output as *state*. Basically, this approach is suited for any cortical activity patterns that can be reliably detected in EEG data, not necessarily restricted to two patterns.

Our hybrid BMI employs the P300 potential and event-related (de)synchronization (ERD), which are both common in many BMI applications (see [3] for an extensive overview on EEG components for BMIs). While the P300 potential is triggered by stimuli and always time-locked to an event, ERD

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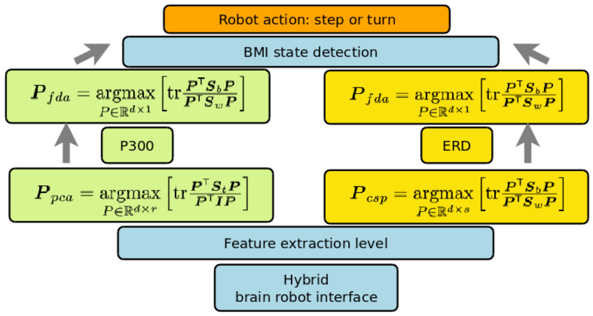

Fig. 1: Schematic illustration of the state detection process in the hybrid BMI.

can be produced volitionally by a human without external cues.

State detection The individual classifiers for P300 and ERD detection are trained in advance. The training data for each classifier is acquired during independent sessions. For the P300, only one short off-line session is needed prior to using the interface. In case of ERD, training is not only limited to machine learning, but also the human needs to learn to produce ERD volitionally. Thus, the human user needs to acquire a new mental skill. This skill demands some feedback-guided training, for example in a visual or auditory modality[4].

Classifier parameters are optimized subject-specific on the training data. In both cases (P300 and ERD), feature extraction and classification methods are linear. We use principal component analysis (PCA) for the P300 and common spatial patterns (CSP) for ERD, which are both approved methods in the context of on-line BMIs [5], [6], [7]. The subsequent classification step is done by linear discriminants (FDA). All three methods can be formulated as linear optimization tasks [8] that require solving a generalized eigenvalue problem on the covariance matrices of the data. In case of PCA, an unsupervised method, the second matrix becomes the identity matrix. CSP and FDA are both trained in a supervised fashion. Precisely, the FDA can be described as a special case of the CSP where the output dimension is fixed to 1. By solving these three optimization tasks on the training data, four projection matrices are obtained for use in the final system, two for each processing pipeline of the hybrid system. Fig. 1 illustrates the state detection process.

We have evaluated our method for hybrid classification in a simple benchmarking setting as we reported in [9].

III. THE BRAIN-ROBOT ASSISTANT SYSTEM

Humanoid robots are a challenging platform for a BMI. We use *Honda's Humanoid Research Robot*, one of the most advanced humanoid robots currently available. This robot is endowed with sophisticated internal controllers for walking and for controlling the upper part of the body (whole body motion, WBM [10]) including solving the inverse kinematics problems and self-collision avoidance.

We defined a set of high-level action units. Currently, these action units are “step”, “turn”, ”grasp“, “raise”, “drop”, “carry” and “return”. These units may be combined to form action sequences. The system controller has only direct access to these units. All detailed parameters, including kinematic computations, are fixed by the robot's internal WBM controller. The constructed action sequences are suited to accomplish simple, every-day tasks, like grasping an object and bringing it to the human. This is useful, for instance, in a scenario where the robot assistant helps the user in a shop to collect desired items. We use such a simplified shopping scenario because it is a task with a high practical relevance. Currently, the system is implemented in the way that the user may navigate the robot through the store by means of BMI control to select the items he/she wants to collect, while grasping and returning the selected items is accomplished autonomously by the robot. For navigation, the user can select one out of four directions (forward, backward, right, left) to let the robot execute single steps, or to turn in place to the right or left side. Stepping is controlled by the P300 component, turning by imagining a movement of the right or left hand (ERD). Thus, only high level actions need to be controlled explicitly.

IV. EXPERIMENTAL SETTING

Environment All experiments were conducted with the real, physical robot. For testing our system in a controlled fashion while allowing for a realistic task, we created a simplified “store“ in our lab. The “store“ consists of 3 shelves, arranged at three sides of a rectangular area. Ten baskets in different colors are placed on these shelfs. Fig. 2 shows screenshots from the robot simulation. The setup visualized in the images is equivalent (including size and distance relations) to the real setup in our robotics lab during the experiments. The robot is endowed with a map of the store, such that it can act in the ”store“ without the need for additional sensory (e.g. visual) information. This would overload the complexity of the overall system in this initial testing phase.

Task The task of the BMI user is to collect five out of the ten “baskets“ by navigating the robot close to the item. The items and the order of collecting them is fixed by the experimenter and equal for each subject. This is essential for inter-subject comparability of the sessions, although it limits the participant's freedom of how to use the interface. The subject is seated in a chair at a position that enables him/her to see the whole scene. Two computer screens are placed on the floor in the participant's field of view. One is used to show a ”shopping list“ providing the sequence of baskets to collect. The other screen is used to show the stimulus presentation to evoke P300 potentials. As common for P300-based BMIs, the visual stimuli (here arrows indication the stepping directions) flash in arbitrary order. The user focuses attention onto the stimulus of his/her choice, such that this target evokes a neural response while the others do not. For each action, he is free to choose between attending to the stimuli or ignoring them; thus, requesting the robot to either step or turn. Stepping is possible in the four directions (indicated by the stimulus arrows): forward, backward and sidesteps to the left or right side, resulting in a discrete mapping of class

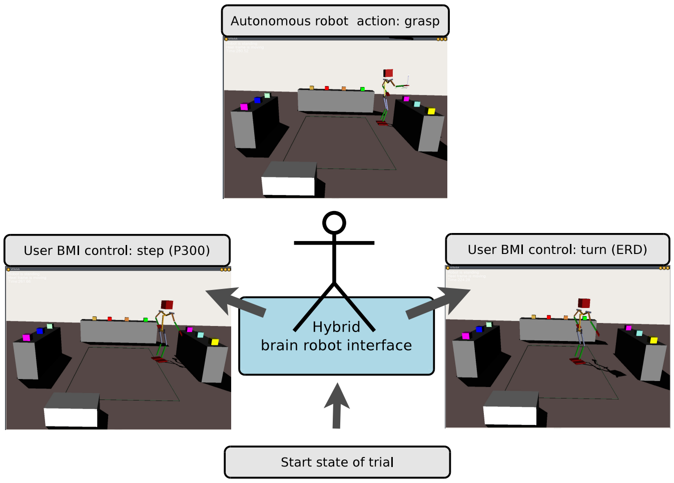

Fig. 2: Screenshots from the robot simulation at different stages of the scenario. The participants had the same view on the scene in the lab. Note that all experiments were conducted with the physical robot in the lab.

labels. Turning, however, is accomplished in a continuous fashion. The real-valued class confidence is translated into an angle that is proportional to the degree of confidence.

Participants Seven participants took part in the study, all male, aged between 21 and 40. One participant was excluded from quantitative analysis such that six valid sessions with complete data are considered for evaluation. All results reported here are based on these six data sets. One participant had already used our BMI before in a different study, all others were naive to BMI usage.

Preparations We used a setup with 16 electrodes, mounted at the locations Fz, F3, F4, Cz, C3, C4, C5, C6, CP3, CP4, Pz, P3, P4, PO7, PO8 and Oz, according to the extended international 10-20 system and referenced to the mastoids (A1, A2). All impedances were below 5 kΩ. Data was acquired with a gUSBamp (Guger Technologies) EEG amplifier at a sample rate of 256 Hz.

All participants had to train the skill of motor imagery (MI) to achieve a satisfactory degree of control over their ERD pattern. Therefore, they conducted three sessions of pure MI training on different days, with about a week pause between. On the day of the experiment, an off-line P300 session was completed for gathering P300 training data and another shortened MI training. Afterwards, the session with the real robot started. The whole experiment including electrode preparation took about 2.5 hours per person.

Robot experiment The experiment starts with the robot standing at its starting position (a defined place in the middle of the ”store“), averted from the subject. The sequence of actions (BMI or system controlled) executed to collect one basket is called a *trial*. During a trial, the user can navigate the robot as long as it stays in the BMI zone. When the robot finishes a ”step” or ”turn” action, the system triggers a new P300 stimulus presentation and requests a new state decision from the data processing module. For safety reasons, the robot will only leave the BMI zone and step close to a shelf when a basket has been reached and the robot prepares for grasping. For a basket to be considered selected, the Euclidian distance between the robot and the object must be smaller than a threshold. Then, the robot will execute the grasping action autonomously and carry the basket to a box, where all items are collected. Afterwards, it returns to its starting position and the BMI control for the user is re-enabled. This procedure is iterated until all five objects have been successfully collected and placed in the box.

V. RESULTS AND DISCUSSION

The evaluation of the system performance relies on four major aspects:

1) A comparison of the number of actions (steps/turns) needed to select a basket using the brain interface with the ideal, minimal number of actions required (given perfect knowledge about the environment).
2) The variance among the participants.
3) The number of actions compared to the expected number of correctly classified states (determined from our previously reported evaluation study [9]).
4) The relation between steps (P300 states) and turns (ERD states) during the trials.

The ideal, minimal number of actions was determined for each trial. Table I gives the mean number of actions per trial, averaged over all participants and also the ideal, minimal number of actions. As could be expected, the number of steps needed when using brain control is significantly higher ($t=6.82$, $p<0.001$) than the ideal number. However, classification of EEG data in a BMI is never perfect. In our evaluation study with the hybrid BMI, we reported an overall state detection error rate of 0.23. We did not record the ground truth during the sessions, because this would have required that the user reports his intention after every state detection by the system, which would have disturbed the flow of the experiment. As a first approximation, the state detection error rate is considered to be the measure for the expected performance of the system in terms of classification error. Thus, we consider 23% of all actions to be caused purely by state detection errors of the system and not by the user's intent. Given the mean number of 66.68 actions for all trials, 51.34 actions remain. This number is 1.7 times higher than the ideal number of actions (30). However, given the complexity of the setting with a physical, almost human sized robot which has to be navigated in a real environment, this number is satisfying. None of the participants have had experience with Honda's Humanoid Research Robot before. In addition, a BMI is a totally novel type of interface for human-machine interaction for the participants.

Interestingly, one participant accomplished the whole session without a single turn (ERD state). He navigated the robot purely by stepping. All other participants used a combination of stepping and turning to move the robot towards the target, which leads to more natural trajectories. The number of actions differs between 55 for the best and 91 for the worst performing participant. The standard deviation

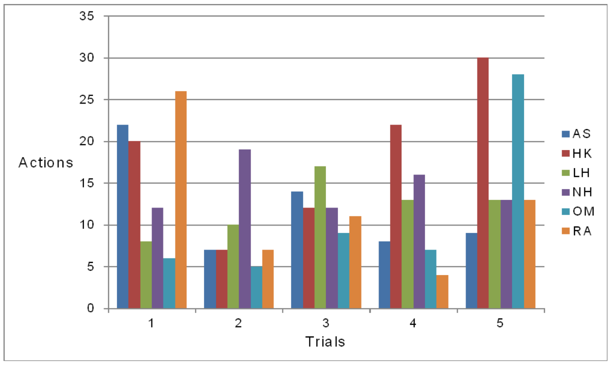

Fig. 3: The bar chart shows the action number for each participant and each trial. The characters in the legend indicate the subject codes.

TABLE I: The table gives the mean action numbers (averaged over all participants) needed to reach each item. For comparison, the minimal numbers of actions are also given.

	BMI control			Perfect control		
Trial	All	Steps (P300)	Turns(MI)	All	Steps	Turns
1	15,67	10,17	5,50	5	4	1
2	9,17	7,00	2,17	5	4	1
3	12,50	7,67	4,83	7	3	4
4	11,67	6,67	5,00	6	3	3
5	17,67	9,00	8,67	7	3	4
All	66.68	40.51	26.17	30	17	13

between subjects is σ=12.01, indicating that all participants were able to accomplish the given task in a comparable fashion. Fig. 3 gives the detailed numbers of actions that each individual participant needed during each trial.

Some participants seemed to have difficulties with performing ERD in this complex setting. This assumption arises from a visual analysis of the session (video recordings were made during all sessions). During some trials, a participant tried to turn the robot towards the target, but the robot turned the other way round. This behavior is not consistent with the expected error rates for the state detection, which should be around 0.3 for the ERD part alone. Therefore, we presume that the difficult task has an influence on the ability of the users to reliably produce ERD patterns when they intend to. In contrast to this, the P300 pattern appears to be unaffected by the complexity of the control task. Indeed, these observations are in-line with the neuro-physiological mechanism of both patterns. On the one hand, the automatic, stimulus driven P300 potential does not demand much additional cognitive load and hence saves the cognitive resources needed to deal with the complex robot control task. On the other hand, the learned, volitional production of ERD pattern requires the allocation of additional resources, which might be difficult if the task as such is complex. However, it should be possible to attenuate this issue by more user training for ERD, in particular while using increasingly complex control or feedback settings.

VI. CONCLUSION

We implemented an advanced approach towards a sophisticated assistive system, providing a state-of-the-art humanoid robot with elaborated capabilities that can act as a personal assistant for severely handicapped people. We developed a complex, multi-functional hybrid brain-robot interface that provides a communication channel between the human and the robot, such that its (otherwise autonomous) actions or behaviors may be manipulated by the human user if necessary. We conducted an empirical study with *Honda's Humanoid Research Robot* in our robotics lab where we employed an every-day task, shopping, to show the functionality of the overall system. All participants were able to reach a satisfactory degree of control with the hybrid brain interface and to successfully accomplish the given task. Furthermore, all but one participant fully exploited the hybrid nature of the system by switching between the P300 and ERD pattern when needed. To transfer this system from the lab into the real world, it is necessary to combine the current implementation of the system with additional functions, like dynamic scene perception, object recognition and path planning. Advanced methods are already available for these functions. In the near future, humanoid robots can, thanks to their embodiment, act as personal assistants for motor impaired people. The robotic assistants can execute motor tasks that these people are no longer able to perform themselves. This will help them to retain more autonomy about their own actions and live a more independent life which, consequently, can largely improve their overall quality of life.

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