Towards Hierarchical BCIs: Combining Motor Imagery and Evoked Potentials for Robotic Control

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Motivation:

- Evoked potentials provide a relatively accurate way of selecting between a large number of classes in electroencephalogram (EEG) based BCI systems [1]. However, due to their reliance on external stimuli, they are unsuitable for fine-grained control. 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 [2].
- Research in our lab is focused on 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 system 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 a hierarchical BCI system for controlling a humanoid helper robot where new lower level behaviors are learned via imagery and invoked 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.

References:

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Methods:

- EEG signals were recorded from 16 electrodes placed over sensorimotor and visual areas from 4 able-bodied volunteers while performing cue-guided motor imagery (MI, 2-classes) and focused attention P300 (2/4-classes, 8 flashes per class) tasks. Images used to evoke the P300 were arranged on the screen in a 2x2 grid and highlighted for 125 ms every 250 ms. Four runs, each with 20 imagery trials and 12 P300 trials (4 per class), were recorded.
- For the imagery task, classes were discriminated using common spatial patterns (8-30 Hz, 1 projection) and Fisher's linear discriminant analysis [3].
- For the P300 task, 1-second EEG segments (0.5-8 Hz) following each flash were spatially projected (3 filters) and classified by a support vector machine (SVM) as target/nontarget; the image with the highest number of hits was selected at the end of a trial [1].
- The methods were trained with the data of runs 1 & 2 (for simplicity, parameters such as the regularization parameter for the SVM were not tuned for subjects and were based on prior experiments) and evaluated off-line on data from runs 3 & 4.

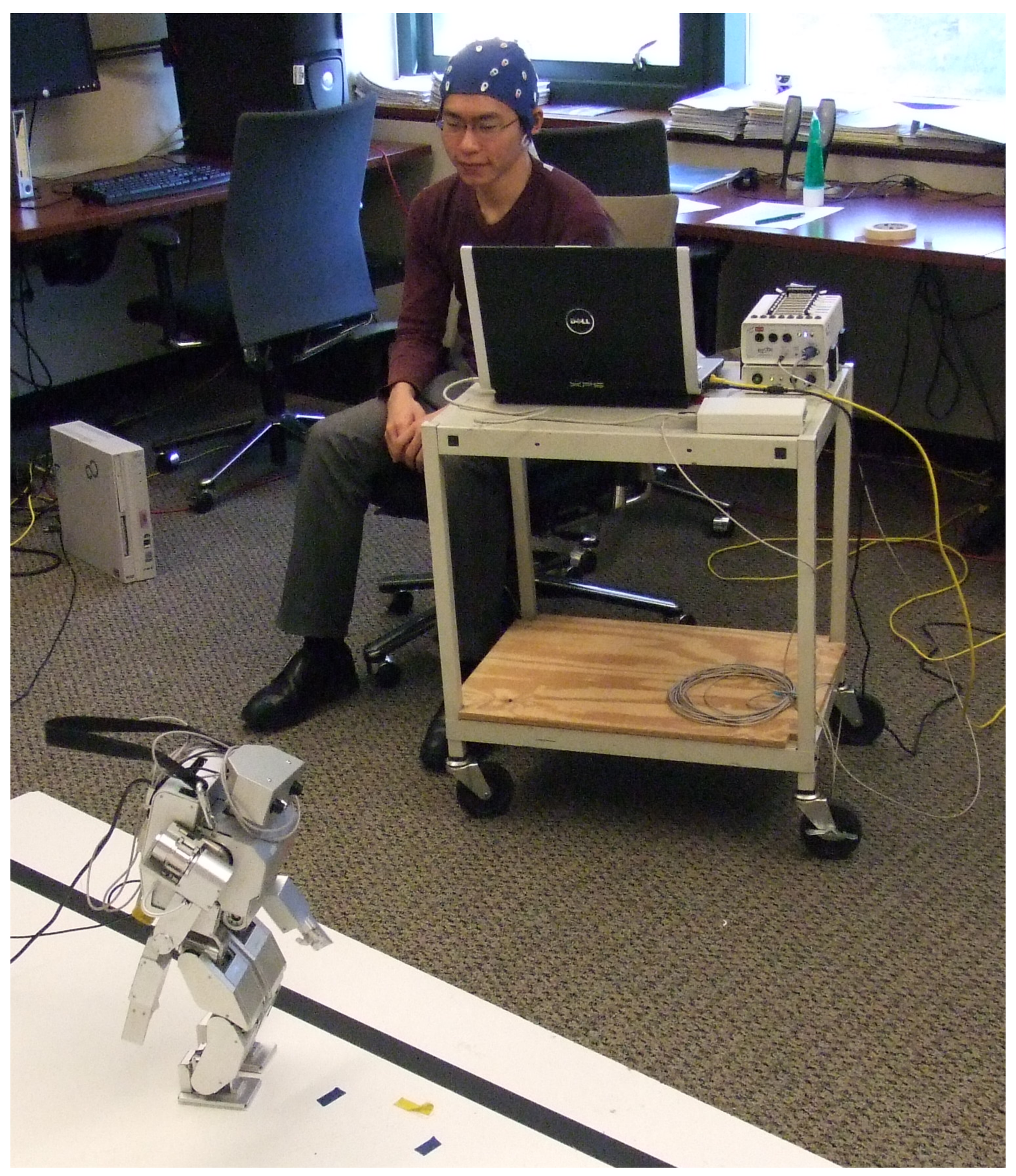

Fig.1. Imagery-based control of a humanoid robot.

Results:

- Averaging over subjects, accuracies (standard deviations) for 2-class imagery, 2-class and 4-class P300 of 76(8)%, 96(5)% and 84(5)% were computed. Corresponding theoretical 2 and 4 class chance levels are 50% and 25%, respectively.

Discussion:

- The preliminary results from our offline study suggest that users can switch between the modalities of motor imagery and evoked potentials, and achieve reasonably high accuracies in each case.

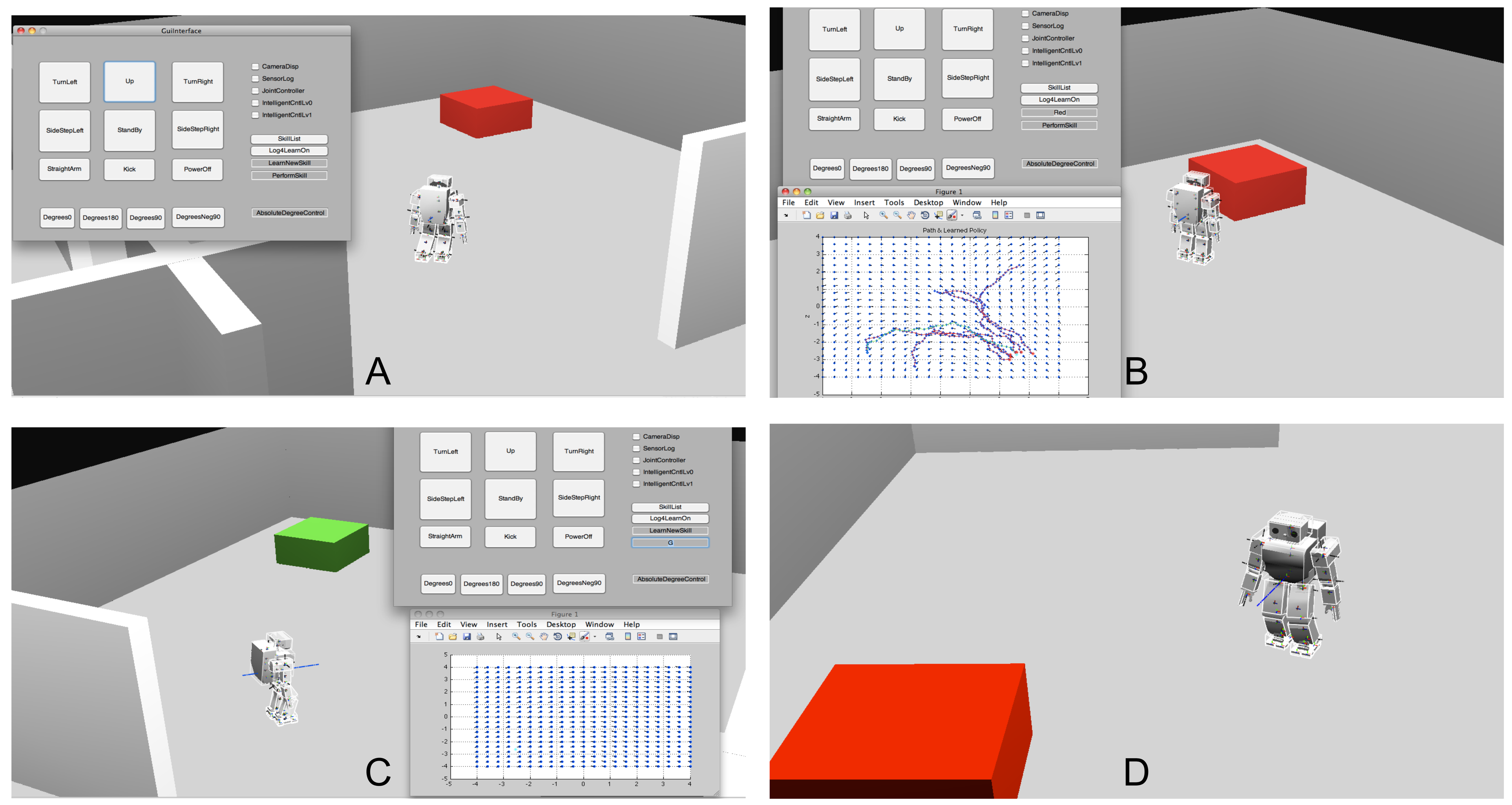

Fig. 2. Simulation environment for learning new behaviors. (A) Guiding the humanoid robot to a goal location using low-level commands. (B) Learning the demonstrated low-level behavior. (C) Selecting the learned behavior from updated menu. (D) Executing learned behavior as a high-level command.

Conclusion and outlook:

- Our results constitute a first step towards building a hierarchical BCI system based on combining imagery and P300 for controlling a robot.
- The specific robot we are using is a Fujitsu HOAP humanoid robot (Fig. 1) which is equipped with vision and other sensors, and possesses the ability to walk, side-step, pick-up and drop off objects. Our current experiments are focused on investigating whether users can maneuver the robot using imagery 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. The BCI then uses this trajectory to abstract the command while the robot learns to map its percepts to appropriate navigational actions. On a subsequent run, the robot is commanded to navigate autonomously to the kitchen based only on a higher level P300-based command. We are testing this paradigm in a simulated environment (Fig. 2). In the proposed approach, the best performance is achieved only when the BCI and the controlled device (the robot) learn simultaneously from the user's inputs, a topic of particular importance to the BCI community.