Interactive Hierarchical Brain-Computer Interfacing: Uncertainty-Based Interaction between Humans and Robots

M. Chung[1], M. Bryan[1], W. Cheung[1], R. Scherer[2], R.P.N. Rao[1]

[1]Neural Systems Lab, Computer Science & Engineering, University of Washington, Seattle, USA
[2]Institute for Knowledge Discovery, BCI-Lab, Graz University of Technology, Graz, Austria

Abstract

Current non-invasive brain-computer interfaces such as those based on electroencephalography (EEG) [1] suffer from the problem of low signal-to-noise ratio, making fine-grained moment-by-moment control tedious and exhausting for users. To address this problem, we have previously proposed an adaptive hierarchical approach to brain-computer interfacing: users teach the BCI system new skills on-the-fly and these skills are later invoked directly as high-level commands, relieving the user of tedious lower-level control. However, the high-level commands learned from user demonstrations are often not reliable due to incomplete or insufficient data. In this paper, we address the unreliability of such learned high-level commands by proposing an interactive hierarchical BCI. The proposed approach utilizes an uncertainty metric in the learning algorithm to determine whether the learned high-level command is reliable enough to be performed in the present context. The BCI system interacts with the user to make the best decision at each stage. We illustrate the approach using an interactive hierarchical BCI for controlling a simulated wheeled robot. In a study involving two human subjects controlling the robot in a simulated home environment, each subject successfully used the system to complete a sequence of five different navigational tasks. Our results suggest that interactive hierarchical BCIs can provide a scalable and robust way of controlling complex robotic devices in real-world environments.

1 Introduction

Moment-by-moment control of electroencephalogram-based (EEG) brain-computer interfaces (BCIs) over long periods of time can be a significant cognitive load and can exhaust the user. Therefore, EEG signals have often been used to select a task that can be semi-autonomously performed by an application (e.g., control of a humanoid robot in [2]). Recently, we introduced an adaptive hierarchical approach to BCIs, which combines the flexibility of fine-grained moment-by-moment control with the ease of high-level learned commands [3]. By incorporating learning algorithms, high-level commands (tasks that can be semiautonomously performed) can be learned from a user's lower-level control demonstrations. To illustrate the approach, we have focused on navigation problems, i.e., we teach robots new skills such as "Go to location A" by navigating the robot using the BCI to the desired destination. In order to create an internal representation, the machine needs a number of training trials. BCI control, however, is slow compared to manual control and thus data collection is very time consuming. As a result, training data is scarce, which makes accurate predictions difficult and the execution of high-level commands unreliable.

To overcome this problem, we introduce an interactive approach to hierarchical BCIs. We propose a system which possesses the ability to interact with the user whenever user guidance is required to successfully complete a task: the system's behavior relies on an uncertainty metric. The measure of uncertainty is obtained using a Gaussian Process (GP) model [4] for learning the high-level commands. When the uncertainty in a given region is too high, the BCI asks the user for further guidance rather than continuing to execute the unreliable and potentially dangerous high-level command. When the uncertainty in a region is low, after the user's guidance, the

BCI takes control from the user to complete the issued high-level command. The uncertainty-based interaction in hierarchical BCIs not only helps the system cope with unreliable high-level commands but also provides a smooth interface that combines the strength of the user and of high-level control.

We present results from user studies involving two human subjects who successfully completed five consecutive navigational tasks assigned to them. The users taught, controlled, and interacted with a wheeled robot in a simulated home environment. Our results provide a proof-of-concept demonstration that interactive hierarchical BCIs may provide a robust and flexible approach to controlling complex robotic devices.

2 System Architecture

The hierarchical BCI consists of three closely coupled systems: a SSVEP-BCI, the learning framework and the wheeled robot. Several enhancements were included compared to the system proposed in [3]. First, for the SSVEP-based BCI we use a support vector machine (SVM) classifier instead of selecting SSVEPs based on the absolute power in the spectrum. Second, we replaced the simulated Fujitsu HOAP-2 humanoid robot with a simulated K-Team Khepera wheeled robot. Since our experiments are focused heavily on the navigational aspect of mobile robots, a wheeled robot is more suitable for this purpose. The wheeled robot is pre-programmed with basic navigational functionalities such as driving forward, turning left, turning right, etc., and basic obstacle avoidance functionality. Third, the GP algorithm was used for learning high-level commands from logged position data during user demonstrations. During execution of a high-level command, the robot queries the user for navigation direction based on its uncertainty in its current position. When GP model is used, one obtains both a predicted mean value as well as the variance of the prediction. This variance can be related to the "confidence" in the learned model: high variance implies low confidence in the predicted navigational command and vice versa. For the current implementation, we used a simple threshold (determined empirically) to decide whether the robot should ask the user for guidance or take control from the user to finish a commanded tasks. Last, hierarchical adaptive menu structure [3] was updated to incorporate changes made in the other components.

3 Experimental Procedure

Two able-bodied male subjects (ages: 19, 21) participated in the study, which was approved by the University of Washington Institutional Review Board. All subjects gave written informed consent. Subjects did not have any experience with using our interactive hierarchical BCI system. However, they had been test subjects in SSVEP-based BCI experiments in the past.

The experiment was conducted over three days. On the first day, the subjects' SSVEP responses were characterized and the subjects were allowed to familiarize themselves with the SSVEP-BCI control. On the second day, subjects used the entire system to perform two assigned navigation tasks. The first task was teaching the robot how to navigate from the starting location, room A (upper left corner), to room B (upper right corner), which we called "skill1" (see Figure 1). The second task was teaching the robot how to navigate from its current location, room B, to room C (lower left corner), which we called "skill2". With skills 1,2 the subject provided only one training example. On the third day, subjects were assigned three different navigation tasks. The third task was navigating the robot to room B from its current location, room C, by using learned skill1. The fourth task was teaching the robot how to navigate from its current location, room B, to room D (lower right corner), which we called "skill3". The last task was navigating the robot to room C from its current location, room D, by using skill2.

Note that a skill represents a goal and a set of trajectories to reach that goal. This implies that a skill can be robust with respect to starting position. For instance, once a user defines skill1 with a goal of room B and a starting position A, they add additional information to that skill on the third day to teach the robot to navigate to B from a third position, C.

To graph the confidence metric of learned high-level commands and the interactive behavior of the system, we collected navigational traces and and plotted confidence maps computed from the learned GP during the performance of the assigned tasks (Fig. 1).

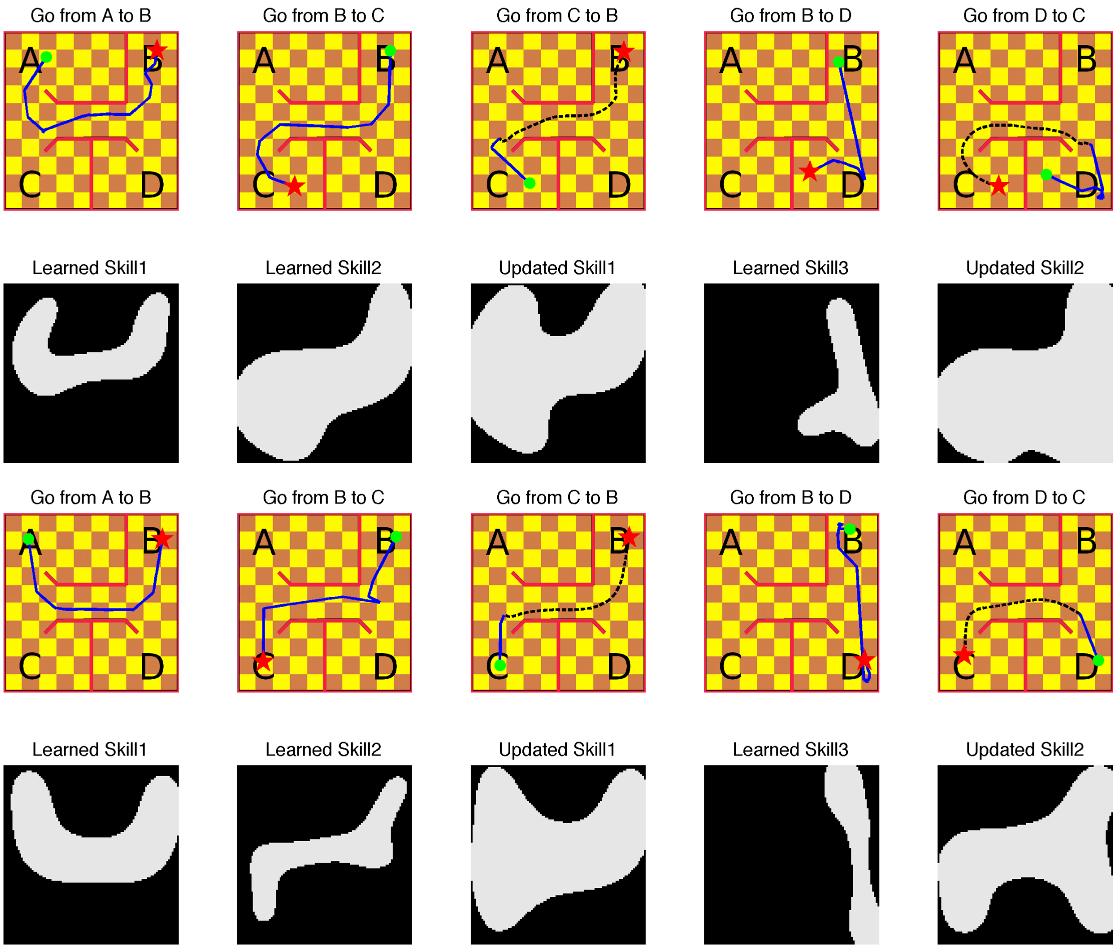

Figure 1: **Navigational traces and learning in the hierarchical BCI.** Columns correspond to assigned tasks. The first two rows are results from the first user and last two rows are results from the second. The first and third rows indicate actual navigational traces from the user. Solid lines are paths navigated by the user and dotted lines are paths navigated by the autonomous system. Dots mean starting positions and stars mean end positions. The second and fourth rows are confidence maps of the high-level skills learned during each task. Bright regions are high-confidence areas and dark regions are low-confidence areas.

4 Results

Both subjects were able to use the interactive hierarchical BCI to complete the five assigned tasks. The trace plots provide several interesting insights. First, the navigation traces from the autonomous system during the third and fifth tasks resemble the initial demonstrations provided by each user in the first and second assignment. This means the system is adaptive and can generalize based on the demonstrations provided by the user. Second, the generalization of performance is highly dependent on pre-chosen confidence thresholds on the variance of GPs. This is partially because the small quantity of training data implies relatively large changes when new data is added. (Usually, training data includes more than one or two datasets.) Since the goal of this system is to learn new high-level skills on-the-fly, the BCI system starts learning after the very first example. The generalization process is determined by the parameters chosen to determine the high-confidence regions (i.e. white regions).

5 Conclusion

BCIs for robotic control have in the past faced a trade-off between cognitive load and flexibility. More robotic autonomy implied coarse-grained control and less flexibility, while fine-grained control provided greater flexibility but higher cognitive load. We propose a hierarchical approach which overcomes this tradeoff by combining the advantages of these two approaches. We introduced interactive components to increase the robustness of hierarchical BCIs against unreliable high-level commands.

Our results from the user studies using EEG-based interactive hierarchical BCIs confirms that (1) users can use the interactive hierarchical BCI to train a robot in a simulated environment, allowing learned skills to be translated to high-level commands, (2) the high cognitive load associated with fine-grained control can be alleviated by storing user-taught skills in a learned model for long-term use, allowing the learned skill to be selected and executed as a high-level command, (3) a probabilistic learning model (e.g., GPs) can be used to mediate the switch between high-level autonomous control and low-level user control, safeguarding against potentially catastrophic accidents, and (4) the hierarchical architecture allows the user to simultaneously control multiple devices, opening the door to multi-tasking BCIs. Our ongoing efforts are focused on 1) testing the approach with a larger number of subjects. 2) investigating its applicability to other challenging problems such as controlling a robotic arm with grasping capabilities. 3) exploring other types of brain responses (P300 and imagery) to achieve more natural and intuitive control.

Acknowledgments

This work was supported by the National Science Foundation (0622252 & 0930908), the Office of Naval Research (ONR), and the ICT Collaborative Project BrainAble (247447).

References

[1] J.R. Millan, F. Renkens, J. Mouriño, and W. Gerstner. Noninvasive brain-actuated control of a mobile robot by human EEG. *Biomedical Engineering, IEEE Transactions on*, 51(6):1026–1033, 2004.

[2] C.J. Bell, P. Shenoy, R. Chalodhorn, and R.P.N. Rao. Control of a humanoid robot by a noninvasive brain–computer interface in humans. *Journal of Neural Engineering*, 5:214, 2008.

[3] M. Chung, W. Cheung, R. Scherer, and R.P.N. Rao. Towards hierarchical BCIs for robotic control. *Neural Engineering, 2011. NER'11. 5th International IEEE/EMBS Conference on (to appear)*, 2011.

[4] C.E. Rasmussen. Gaussian processes in machine learning. *Advanced Lectures on Machine Learning*, pages 63–71, 2004.