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Task Level Hierarchical System for BCI-enabled Shared Autonomy

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***Abstract*— This paper describes a novel hierarchical system for shared control of a humanoid robot. Our framework uses a low-bandwidth Brain Computer Interface (BCI) to interpret electroencephalography (EEG) signals via Steady-State Visual Evoked Potentials (SSVEP). This BCI allows a user to reliably interact with the humanoid. Our system clearly delineates between autonomous robot operation and human-guided intervention and control. Our shared-control system leverages the ability of the robot to accomplish low level tasks on its own, while the user assists the robot with high level directions when needed. This partnership prevents fatigue of the human controller by not requiring continuous BCI control to accomplish tasks which can be automated. We have tested the system in simulation and in real physical settings with multiple subjects using a Fetch mobile manipulator. Working together, the robot and human controller were able to accomplish tasks such as navigation, pick and place, and table clean up.**

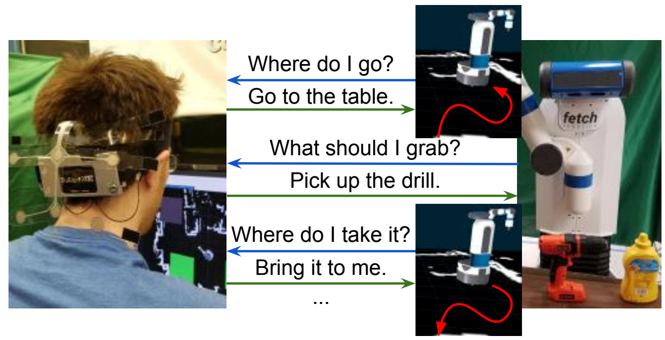

Fig. 1: Our shared autonomy system allows a robot and human to work together to accomplish a task. The robot has sensing, navigation, and manipulation capabilities. The user provides high level commands via a BCI.

I. INTRODUCTION

Shared autonomy is when a human and robot agent collaborate to accomplish a task utilizing their respective strengths. As humanoid robots become more capable, the mode of communication/control between human and robotic agents becomes increasingly important. Humans faced with complex, multi-DOF tasks involving a humanoid can easily become overloaded with navigation, control, and task choice selections. Simplifying this interface is imperative for smooth cooperation and control of humanoids. In this paper, we explore using a Brain-Computer Interface (BCI) as the mode for communicating human intent and interests to the robot as illustrated in Figure 1. BCI, which measures human brain activities, can be used to generate high-level direction from humans while the robot can autonomously handle details related to navigation, control and task-specific actions. We have devised a hierarchical system that divides complex tasks into subtasks allowing the user and a humanoid to jointly accomplish these tasks.

BCI has been an active area of research for a number of decades, yet it has had limited real-world use outside of specialized applications. One of the problems with BCI is false response rates [1]. Further, surveys of users of BCI systems (typically participants of research experiments) highlight that the systems can be fatigue-inducing and frustrating especially because it can be unreliable. In addition, BCI has a limited communication bandwidth [2]. The amount of information (bits-per-minute) derived from typical BCI systems is very low. These, among other reasons, make it difficult to come up with a wide range of use-cases for BCI systems. In this paper, we explore a more reliable BCI interface and address the low bandwidth problem by using shared autonomy and a hierarchical task decomposition approach.

With increased reliability, BCI provides an intriguing method for controlling remote agents. Human operators can easily become overloaded as task responsibilities increase. By using a BCI, possibly in concert with other interfaces, a human operator can begin multi-task control of multiple agents, some controlled by more traditional interfaces, and others using a simple BCI. In addition, BCI recordings typically do not require physical motion from the user which makes BCI suitable for humans with disabilities. Hence, this work finds high applicability in the *Assistive Robotics* space. Beyond that, this work takes steps towards using BCI as a complementary input modality to enhance human-robot interaction even for able-bodied people. While keyboard, joystick, mouse, gesture, and voice are some existing modes of communication (conventional input devices), BCI could be added to this list. A user in a control room built to accomplish a complex task with different knobs/controls but just two hands can use the BCI as a complementary input modality.

This work creates an infrastructure that enables any robotic system to be configurable to take BCI inputs enabling humans to collaborate with robots to accomplish tasks in a robust way. Our hierarchical system uses Steady-State Visual Evoked Potentials (SSVEP), a reliable BCI technique, to take guidance cues from the human whenever the robot is uncertain about the high level task while the robot autonomously handles the low-level tasks such as navigation, grasping, and

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manipulation.

Tasks are typically subdivided into modules for the robot to achieve and whenever the robot is unsure of what to do, it presents the options as multiple flashing visual signals from which the user can make a choice using the BCI. To demonstrate the strength of this infrastructure we have designed an experiment for a home-assistant robot which accomplishes different tasks by polling the user for choice selection between different options. Robot strengths are leveraged to the fullest as the user input is only polled occasionally to resolve the robot's uncertainty.

The framework presented can use different BCI techniques at different layers to get human input into a robotic system. As new and different BCI technologies are developed, they can be interchanged and adopted into different layers of the hierarchy. Our key contributions are:

- Novel use of a BCI to control a humanoid robot doing a variety of tasks.
- Shared Autonomy system that leverages the strengths of both humans and robots.
- A hierarchical system that divides complex task into subtasks, allowing the robot to focus on simpler primitive tasks, while allowing the human operator to control task flow and decision making.
- Intuitive screen-based visualization of the task to enhance operator understanding and interaction.
- Experiments with human subjects, including quantitative and qualitative measures of success.
- A benchmark simulated environment setup for assessing robustness of BCI-controlled robotic applications and tracking the growth of the underlying BCI technologies.

II. BACKGROUND AND RELATED WORKS

A. Brain-Computer Interface

There are different BCI technologies for monitoring brain activities [3] [4] [5] [6] [7] [8]. Two factors influence our choice of BCI technology for this project. The first factor is *Portability*. EEG and fNIRS are typically portable systems while the last four require expensive, immobile and elaborate setup. The second factor is *non-invasiveness* to avoid surgical interventions in acquiring human brain signals. Invasive techniques like electrocorticography (ECoG) and intracortical electrode recordings were ruled our for this project. EEG and fNIRS meet these two key requirements but EEG was our preferred choice because fNIRS has an inherent detection delay since the measured hemodynamic response occurs a few seconds after the originating brain activity.

There are many different neural response patterns that the EEG can monitor and measure. These include: Steady-State Visual Evoked Potentials (SSVEP) [9], Motor Imagery (MI) measuring sensorimotor rhythms [10], Error related Potentials (ErrP) [11] [12], P300 responses [13], and Affective States [14] among others. ErrP, MI and affective states are naturally occurring signals while SSVEP and P300 require stimuli to elicit a neural response.

Naturally occurring brain signals are appealing because they do not require stimuli generation but their characteristics vary widely depending on the user, time of day, and environmental conditions. This creates a need for a highly controlled environment and significant training time to tune a classifier. SSVEPs are generated in the brain when humans stare at a visual stimulus oscillating at a frequency above 6 Hz. A BCI user can modulate the SSVEP by focusing attention on one of multiple stimuli presented to the user. SSVEP has been used for various applications including, typing from virtual keyboards [9] , browsing internet (combined with P300) [15], games [16] etc. We focus on SSVEP because it requires no training or calibration, its analysis is fairly simple and reliable, a robust response can be achieved independent of environmental setup and it provides high temporal resolution signals for analysis [17]. These advantages largely outweigh the requirement of stimuli generation. Since our system only requires user input at a few discrete points, discomfort from the flashing stimuli is not an issue.

B. Shared Autonomy

Brain-controlled robots can be broadly classified into two classes based upon their operational modes [18]. In the ***direct-control*** setting, the robots get control signals from humans continuously throughout the entire duration of the task. For example, brain signals can be classified into three motion commands: left, right, forward for a BCI-controlled wheel chair [19] or motion commands for cursor control [20]. Here, the robots are quite simple with little intelligence; the success of the task depend entirely on the human through the BCI. This puts a large burden and requirements on the BCI system which are typically imperfect and limited both in accuracy and bandwidth leading to slow and uncertain performance. With robots becoming cheaper, more capable and reliable, the performance of brain-controlled systems can be enhanced by leveraging the robot intelligence. In the ***shared-control*** setting, the robot system takes a more active role in accomplishing the given task; the robot is able to autonomously carry out tasks only occasionally getting the user's intention [21]. This alleviates fatigue associated with the burden of continuous BCI control by the user.

C. BCI-Robotics Application

While shared control typically entails humans and robot taking turns to drive the system [22], we focus on the application where the robot does the majority of the work while the user only provides guidance to resolve uncertainties or assign tasks. State-of-the-art robots can autonomously execute a diverse range of tasks but can run into cases where uncertainties can be difficult to resolve on their own. The human input through the BCI interface is invaluable for resolving such uncertainties. For example, [23] explores integrating human analysts with computer vision systems to more rapidly label images; reliable human agents handle tasks that the computer vision system outputs with low confidence.

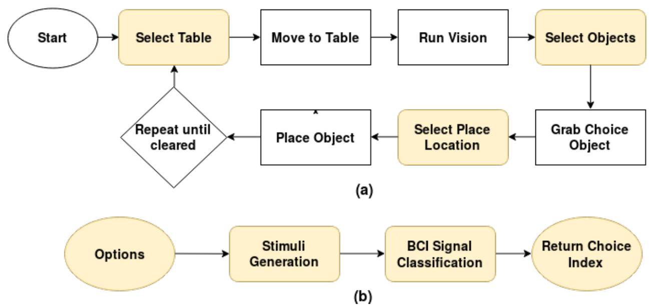


Fig. 2: Flow diagram showing task decomposition for navigation and grasping objects with ”uncertainty-resolving” nodes that gets human input via BCI. (a) An example decomposition of table clearing task into subtasks. (b) Expanded node for resolving uncertainty.

While [24] demonstrated BCI robot control on a non-navigational task (object manipulation), our system incorporates more robotic skills including vision, navigation, and autograsping as suggested in their discussion of future work. While their system uses low-level control to teach the robot, we focus on leveraging a capable robot to achieve a reliable BCI-guided system. Also, while they use custom LED to generate the SSVEP signal, we use in-scene stimuli. In another similar work [25], P300 signals are used to control a humanoid robot. Unlike P300 which requires training a different classifier for each user, we use SSVEP which works with all users without any training.

Our work is similar to the work of Choi and Jo [26] but differs in approach, paradigm, and implementation. Their approach focuses on an inexpensive BCI interface system for humanoid robot navigation and recognition. The hierarchical framework presented in our work looks beyond specific specialized cases but at the broader goal of making any robotic system to be configurable to take BCI inputs and still work reliably. In our system, we use BCI signals exclusively as human input to the system; in contrast, [26] also uses other inputs methods like ”head-turns”, which may be infeasible in some settings or impossible for severely disabled subjects. Finally, we’ve built a much higher level of autonomy into our humanoid robot to enable the robot take an active role in the shared autonomy framework. While Choi and Jo use limited navigation and 2D single object recognition, our robot autonomously maps and navigates its environment, senses its world using 3D vision processing and manipulates multiple diverse objects.

III. Methodology

A. Hierarchical Framework

Since robotics tasks can be decomposed into different permutations and combinations of subtasks (task abstraction) [27], we are able to create an ordered hierarchy of subtasks. For example, a food delivery task can be decomposed into *get food*, *navigate to customer*, *deliver food*. Other tasks such as a table cleaning task can share and use some previously defined subtasks leading to extendable hierarchical structure.

In our hierarchical framework, there are nodes that present the robot with multiple, equally valid options. These ”uncertainty-resolving” nodes take as input the options and prompt the human agent who then returns the chosen option using the BCI. These nodes present the input options as visual stimuli and analyzes the human agent’s brain signal to determine the preferred option. Figure 2 shows the flow for a sample task of moving to a table and grasping an object and placing it in a new location. By reconstructing the building blocks of our hierarchical system, users are able to create various composed task pipelines.

B. Stimuli Generation

When a robot is unsure of the next stage of a task, it can present the options to the user for resolution. Since we use SSVEP as the BCI communication method, these options are presented to the user in visual form (as oscillating visual stimuli). For example, if a robot is unsure of its destination, it can present a map to the user with blinking stimuli overlaid at different locations on the map. Figure 3 shows a typical environment for a home-assistant robot, with multiple rooms, tables within rooms, and objects on tables. Figure 4 shows visual stimuli overlaid on the map to allow a user to choose a location to navigate to. By focusing on one of the stimuli, the SSVEP signal is generated at the occipital region of the brain whose frequency indicates the selected choice. For our system, we split the choice frequency band 6-9.9 Hz across the 2-4 options. For example, 3 options would blink at 6.6, 8.5 and 9.9 Hz. Once the navigation is completed, the robot can present choices for which table to approach, and then choices for which object to pick up, and finally where to place the object.

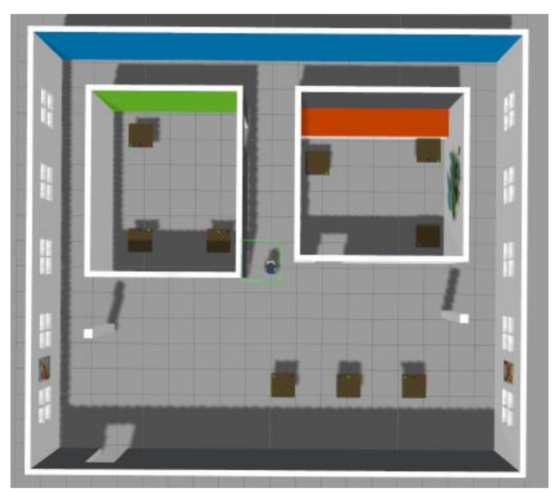


Fig. 3: Model Home environment where robot can interact with human to carry out task in simulated world.

Brain Signal Collection and Processing: We use a wireless EEG Headset–the B-Alert X10 System Sensor–with electrodes located at O1, and O2 (based on the international 10-20 system) with left and right earlobes as the reference and ground. Referential recordings were acquired from both

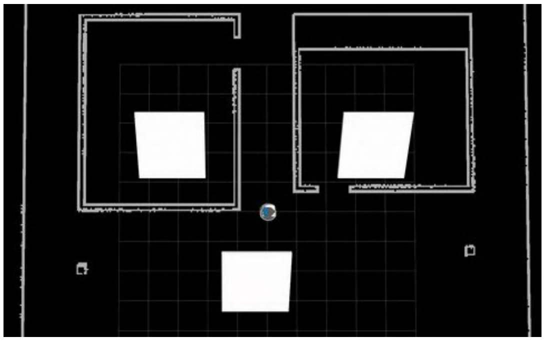


Fig. 4: Home map overlayed with visual stimuli for SSVEP user detection. Each stimulus blinks at different frequency

occiptal electrode sites. The sampling rate was 256 samples per seconds for all channels. The headset wirelessly communicates the signals to the software on the computer. The accompanying driver for the device runs on Windows so we needed to transfer the EEG signals to a Linux based platform that runs the entire setup. We use the Lab Streaming Layer (LSL) software framework to stream the EEG signal for real-time processing.

Data is filtered with a bandpass from 2.5 Hz to 30 Hz. After filtering, we use canonical correlation analysis (CCA) to pick the frequency which is most correlated with the brain signal. The key parameters for SSVEP analysis include channel location, window length, and the number of harmonics[28]. We record brain signals for 5-12 seconds and use 3 harmonics for the CCA analysis.

We recall the CCA definition from [29]: given two sets of data X and Y generated from multivariate random variables $x \in R^{Dx}$ and $y \in R^{Dy}$, CCA finds a projection for each set such that their projections are maximally correlated.

$$(w_X^*, w_Y^*) = \underset{w_X, w_Y}{\arg\max} \operatorname{corr}(w_X^T X, w_Y^T Y) \qquad (1)$$

The recorded EEG signals are passed in as variable X. For Y, we generate sinusoidal data corresponding to each given frequency f_i and also concatenate some harmonics as Y_i. Using CCA, we get the optimal correlation value: $\operatorname{corr}(w_X^* X, w_Y^* Y_i)$. The frequency which correlates the most with the brain signal determines the choice of the user:

$$C = \max_i \operatorname{corr}(w_X^* X, w_Y^* Y_i) \qquad i = 1, 2, ...N \qquad (2)$$

Once a user's intents are detected for the high level tasks, the robot executes until the next uncertainty and the user is queried.

C. Robot Autonomy

We build a number of skills into the robot to allow it to function autonomously. These include navigation, object segmentation and geometric reasoning (vision), and an ability to pick and place objects (manipulation). All of these skills are needed to perform tasks in a home setting.

Navigation: A home-assistant robot has to be able to navigate in its environment. We use a ROS SLAM algorithm package which allows the robot (in this paper a Fetch Robotics mobile manipulator) to use its laser scanner to accurately build an environment model and navigate the environment from source location to destination. A sample map of the environment generated can be seen in Figure 5b.
Vision: Given a table-top scene with multiple objects and little clutter, the robot segments out the different objects on the table using PCL's [30] implementation of euclidean cluster extraction. Each of these clouds are potential candidates to be interacted with. If the robot is unsure of which one to grasp, it prompts the user to select one via SSVEP stimuli. We restrict the clutter in the scene to the level our segmentation can handle. Though not fully implemented for this work, the robot can disambiguate cluttered scenes in stages, starting with coarse over-segmentation followed by more granular segmentation of the user-selected coarse segment.
Manipulation: Once the robot is certain which point cloud to interact with (i.e. grasp), we use an online grasp planner to find a suitable grasp. First, we build the object's complete 3D model using the partial view from the robot. To do this, we use a Deep Learning, CNN-based shape completion method developed in our lab that can complete the occluded region of the object given the partial view [31]. Compared to object recognition modules that require a database of known objects apriori, this technique makes the vision system generalize to novel objects the robot might encounter. The shape completion method returns a smoothed 3D mesh which can then be used for online grasp planning. We use the online grasp planner in *GraspIt!* [32] on the detected object. Online grasp planning is important since the robot may not know the object it will encounter ahead of time. With the list of possible grasps generated by *GraspIt!*, we use *MoveIt!* [33] for arm trajectory planning. This enables us to perform arbitrary pick and place operations.

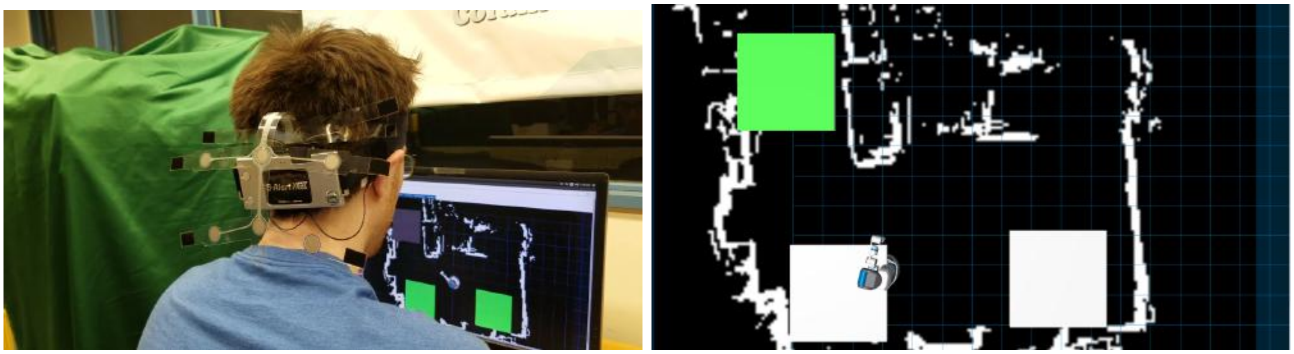
These skill sets make up the robot component of the shared autonomy system. Using these embedded skills of the robot, the user can effectively control and guide the robot to accomplish many tasks needed from a home-assistant robot.

IV. EXPERIMENTS

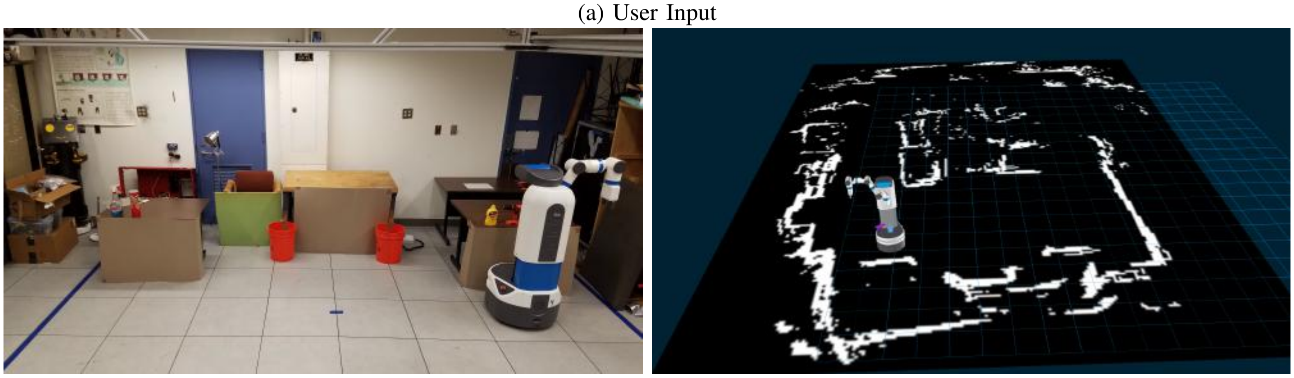
To test our framework, we created environmental setups (both in simulation and real world) that can serve as a benchmark for testing and reporting the performance of BCI systems for robotics application. In these setups, we have a home-assistant robot that can be assigned different tasks in the home environment. The accompanying video submission also gives an overview of the setup and experiments.

A. Simulated Experiment

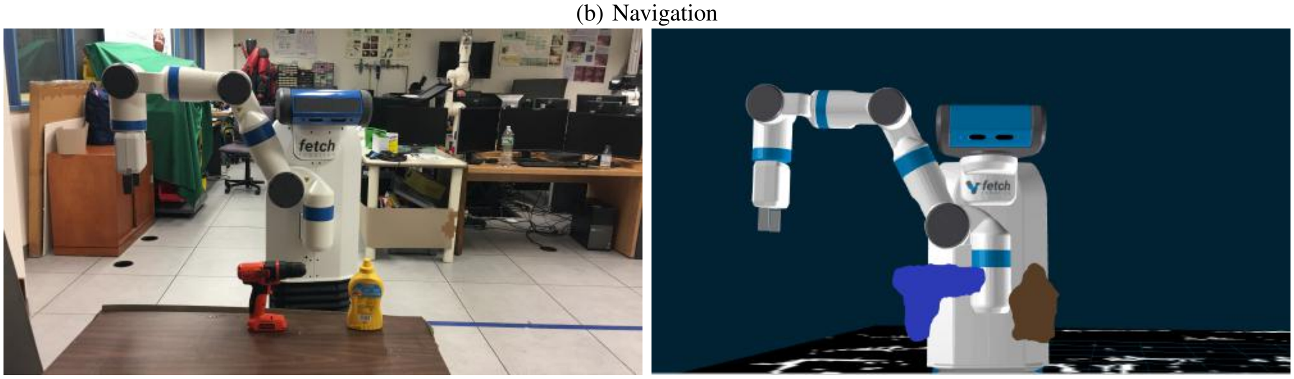
On a mock-up Fetch Robotics [34] building model (see Figure 3) we build a simulated home environment with multiple rooms, tables, and different objects on the tables. The human subject cooperates with the robot to accomplish different assigned tasks. Developing and testing in a simulated environment makes it easier to isolate BCI application



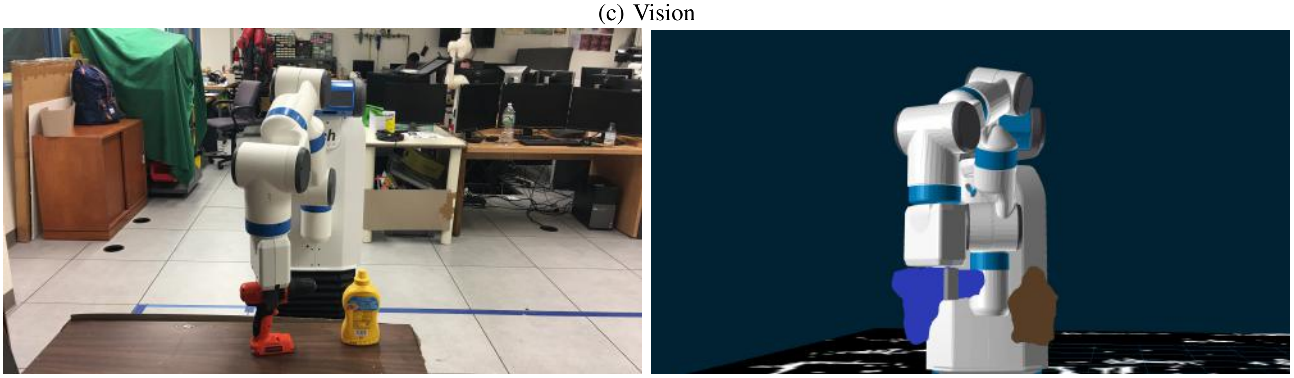
(a) User Input



(b) Navigation



(c) Vision



(d) Manipulation

Fig. 5: Stages of the Table Clean-up Experiment. Left Column: shows live images of the running system. Right Column: shows what is seen by the user. (a) First the robot queries the user to determine which table to approach. (b) The robot autonomously navigates to the indicated table. (c) Visual processing to analyze objects on the table occurs. Object entities on the table are autonomously segmented out and presented to user to choose which object to pick up. (d) Grasp and trajectory planning are done to autonomously determine how to pick the object, and the robot picks up the object. Next it repeats a similar cycle by asking the user where to put the object.

development and provides a codebase and framework similar to the actual system. This work demonstrates the use of a simulated world as a test-bed for developing BCI-enabled robotic systems and as a way to benchmark and compare BCI modalities applied to robotics. We will fully explore the latter point in a future work to compare multiple and hybrid BCI technologies in a similar simulated robotic environment.

Random Task Generation: Different subjects can undertake the experiments a variable number of times. To increase the variation of the experimental tasks and increase user engagement, we use a simple task generator to assign slightly different tasks to the user. An example task is: "Get the robot to pick object [x] from room [y] and place on table [w] in the room [z]." Each of the specific options are randomly picked at the start of a given experiment.

We ran the simulated experiments on two subjects and this revealed the appropriate parameters needed to have a reliable system. For example, we observed that we could achieve 100 percent SSVEP classification accuracy when the number of options were 2 or 3, and the accuracy drops to 75% with 4 options. With the help of the simulated experiments we are able to build a system that works reliably in the real world as described below.

B. Real-World Experiments

Table Clean Up: This task is shown in Figure 5. The user guides the robot to clear objects from a table in a particular order; the robot can either deliver the object to the human or store it away to different locations. While the robot is able to autonomously do parts of this task, it still needs control/guidance to resolve issues such as where the object is in the environment; which of multiple objects to grasp and pick-up; and where to deliver the grasped object. The robot communicates with the user through the BCI to obtain this information at different stages until task completion. Figure 2 shows the flow of the experiment. Recent robotic applications in the travel, tourism and hospitality industries [35] can be cast in a similar hierarchical structure.

Figure 5c shows a table with two objects that each subject had to clear by cooperating with the robot. Once the clean up task is assigned to the robot, the user tells the robot which table to clear (Figure 5a); the robot autonomously navigates to the table (Figure 5b), and runs vision processing to identify the objects on the table (Figure 5c), these are presented as options to the user. After which the robot does grasp/trajectory planning to pick up the selected object. Then the user directs the robot to a new location. This process is repeated to pick the remaining object and place on a different table. Note that this time, there is only one object on the table and the user is not queried to make a choice.

Evaluation: We ran the described experiments on seven subjects. For each subject, we ran the experiment three times and all subjects were able to complete the task. The experimental runs are evaluated based on the following metrics:

- BCI Success Rate (User Input Detection): The reliability of the system is highly dependent on the ability to pick the user's interest (Table I). The BCI system was very reliable, allowing the user to choose the correct option 95/98 times (96.9%).
- Mean Time Distribution Between Stages: We record the amount of time it takes to complete each stage (BCI-recording, navigation, grasping, manipulation). Figure 6 shows the time distribution among the different stages of the experiments and also an idea of how much time is shared between the user and the robot. The amount of time the user spends instructing the robot (12 seconds) is much smaller than the robot takes to plan and execute the main action of each of the stages. Figure 7 shows how accuracy changes as we decrease the duration of recorded BCI signals to help identify optimal recording time. Reducing this time to even 6 seconds shows little loss in accuracy.
- Mean Time to Completion: The total time to accomplish a task ranges from 439s to 543s (mean = 481.3s)

TABLE I: User study results for table cleanup task.

Subject	# of Trials	SSVEP Classification Success (# successful queries / # queries)
1	3	15/15 (100%)
2	3	11/12 (91.7%)
3	3	11/12 (91.7%)
4	3	14/14 (100%)
5	3	15/15 (100%)
6	3	14/15 (93.3%)
7	3	15/15 (100%)
		Total: 95 / 98 (96.9%)

Discussion Two of the subjects initially misunderstood the second lap of the task and sent the robot to the wrong table (the BCI choice though was correct given the user's incorrect assumption). Their subsequent runs went according to the experiment description. From the shared autonomy perspective, there were 7 subjects running 3 trials involving picking up 2 objects for a total of 42 grasps. In 11 cases, the drill was dropped by the robot since it was fairly heavy. In these cases, the task completion time was measured as if the drop did not occur. Once we encountered this problem, we modified the grasp planner to perform a more robust grasp. While not implemented, the robot can sense this failure and could initiate another choice task to pick up the object. Twice we had to end the experiment on the third trial because of poor signal classification which we later found was due to low battery power on the wireless EEG device. We note that the effectiveness of the EEG can be very sensitive to the tightness and placement of the cap. An impedance test is run after putting the EEG cap on the subject to confirm that there is good electrical contact with the scalp. Getting the impedance in a good range typically takes some adjustment to the cap after which there is consistent and reliable signal classification. A portable EEG device that is faster to set up will be a big boost to the BCI research field.

V. CONCLUSIONS

In this paper, we have demonstrated the viability of a reliable BCI-enabled home-assistant robot utilizing shared

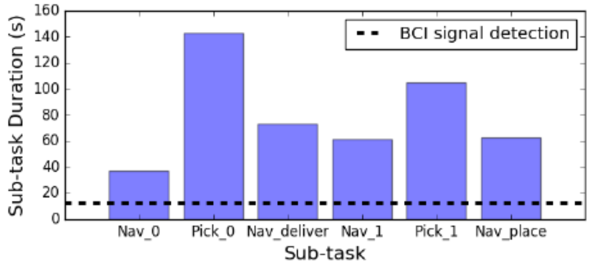


Fig. 6: Mean Time Distribution Between Stages for Table Clean-up Experiment.

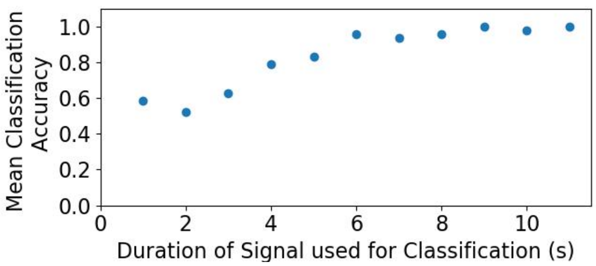


Fig. 7: Prediction Accuracy versus BCI Signal collection duration.

autonomy. Our task level shared autonomy system which only involves the user at discrete times during the task is potentially an improvement over the continuous control of the robot which can be burdensome to the user. We believe that this work also demonstrates an application of BCI to assistive robotics and the framework bears the potential to enable a wider range of BCI applications.

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