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A Collaborative BCI Approach to Autonomous Control of a Prosthetic Limb System

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***Abstract*— Existing brain-computer interface (BCI) control of highly dexterous robotic manipulators and prosthetic devices typically rely solely on neural decode algorithms to determine the user's intended motion. Although these approaches have made significant progress in the ability to control high degree of freedom (DOF) manipulators, the ability to perform activities of daily living (ADL) is still an ongoing research endeavor. In this paper, we describe a hybrid system that combines elements of autonomous robotic manipulation with neural decode algorithms to maneuver a highly dexterous robotic manipulator for a reach and grasp task. This system was demonstrated using a human patient with cortical micro-electrode arrays allowing the user to manipulate an object on a table and place it at a desired location. The preliminary results for this system are promising in that it demonstrates the potential to blend robotic control to perform lower level manipulation tasks with neural control that allows the user to focus on higher level tasks thereby reducing the cognitive load and increasing the success rate of performing ADL type activities.**

***Index Terms*— prosthetics, neural prosthetic system, brain-machine interface, brain-computer interface, semi-autonomous, robotic limb, computer vision, intelligent robotics, hybrid BCI/BMI, modular prosthetic limb**

I. Introduction

There are significant research efforts underway in the area of BCI and Neural Prosthetic Systems (NPS) with a central goal of understanding how the brain functions and how neural signals can be used to control assistive devices [1]–[6]. A specific focus area for many of these efforts involves understanding specifically how the brain maps neural activity to motor control of upper limbs [7]–[9]. This is an important area of research for many spinal cord injury patients (population of over 200,000 in America alone) who lack the ability to perform activities of daily living (ADL) due to upper limb paralysis [10].

Upper arm robotic and prosthetic limb systems are currently available that offer dexterity that is comparable to a human arm and hand in an anthropomorphic size and weight package, such as the Modular Prosthetic Limb (MPL) and other sophisticated manipulation systems [11], [12]. In spite of the technological breakthroughs in manipulation systems, one of the main challenges is the ability to control the high number of degrees of freedom (DOF) available, such as 17 in the case of the MPL. Some cortical control based NPS focus on directly mapping neural activity to limb motion and have demonstrated lower dimensional control [13], [14] as well as higher dimensional control up to 7 DOF of high dexterity systems [15]. While this level of control is revolutionary, empowering for the patients, and typically shows proficient decoding of whole arm movement, it can be limited in high dimensional grasp control at the hand level. Robust hand control over the maximum controllable DOF of a prosthetic system would represent truly dexterous control and further enable functional ADL by these patient populations.

Existing approaches for control of robotic devices include using conventional prosthetic controls (CPCs) (i.e., joysticks, chin switches, etc.), electroencephalograpy (EEG), electrocorticography (ECoG), electromyography (EMG), and direct cortical control through multi-electrode arrays. These methods are matched to a patient depending on a specific disability or functional need. Each methodology has advantages and disadvantages ranging from degree of signal extraction, signal-to-noise ratio, invasiveness of implantation, lifetime, and signal characteristics over time, all of which render a one solution fits all approach impossible.

While traditional control architectures typically map patient signals to direct limb motion, interaction tasks need not require continuous control of a device through a directed trajectory. Several approaches look to assist neuroprosthetic control through the addition of hybrid or semi-autonomous control approaches using a wide variety of interfaces including CPCs [16], eye-tracking [17], [18], EEG, or other BCI [19], [20]. It is evident through the above approaches that by leveraging additional sensors that can ascertain information about the environment or from the patient, improved control of the prosthetic device might be achieved. While these approaches have been successful in reducing the need for continuous user input, in most cases, they focus on one specific patient population or a specific user interface modality. Previously, we have developed a modular control architecture called Hybrid Augmented Reality Multimodal Operation Neural Integration Environment (HARMONIE) that leverages a widely accepted open source software framework (Robot Operating System, ROS) [21]. This system is flexible not only to existing control methodologies, but also incorporates advanced capabilities related to machine vision and perception, object segmentation, and advanced robotic control techniques that would likely realize an increase in performance of neural prosthetic systems [22], [23]. This short paper describes how elements of the HARMONIE

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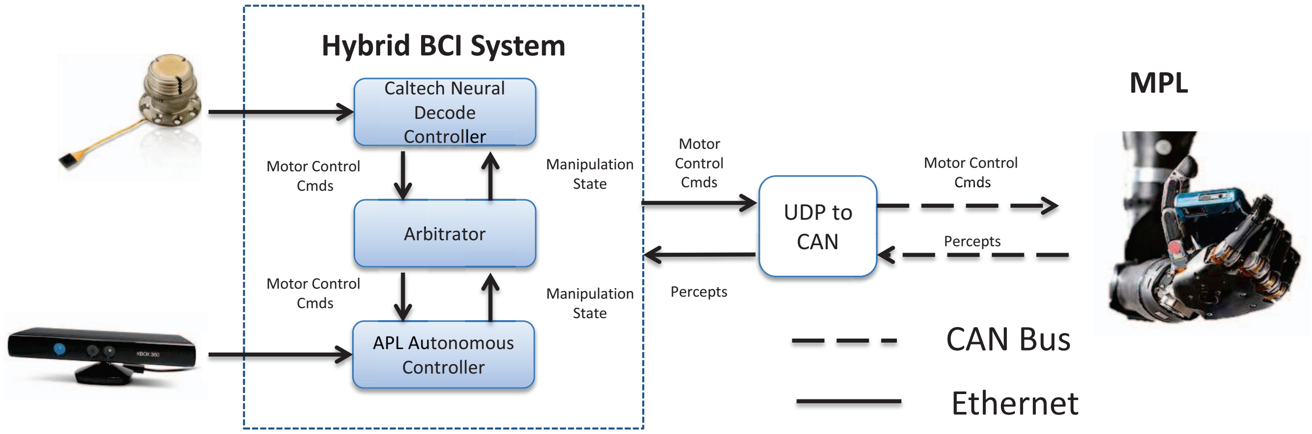

Fig. 1. High-level block diagram presenting an overview of the hybrid BCI system.

system were used to blend computer automation with direct neural control from a spinal cord injured patient in order to successfully perform a reach, grasp and place activity. In addition, we present preliminary results from patient testing as well as discuss the future direction of this work.

II. System Architecture

The system designed to accomplish hybrid BCI control of the MPL is described by Fig. 1 and consists of three key components: the Caltech Neural Decode Controller, the APL Autonomous Controller, and the Arbitrator.

A. Caltech Neural Decode Controller

The Neural Decode Controller acquires neural data from a pair of electrode arrays using a data acquisition system (Blackrock Microsystems, Salt Lake City, Utah, USA). Control of the MPL was coupled to a state-space linear predictor which, in its most general form, may be expressed as

$$\hat{x}_k = \mathbf{A}\hat{x}_{k-1} + \mathbf{B}z_k \tag{1}$$

where k is a subscript denoting discrete time steps, $\hat{x} \in \mathbb{R}^{2M\times 1}$ is the predicted 2M-dimensional kinematic state of the effector containing position and velocity for M DOF; $z \in \mathbb{R}^{N\times 1}$ is an N-dimensional list of features derived from neural recordings; $\mathbf{A} \in \mathbb{R}^{2M\times 2M}$ is the state-space representation of the system dynamics of the effector motion for M DOF; and $\mathbf{B} \in \mathbb{R}^{2M\times N}$ addresses the influence of each feature upon each kinematic variable in $\hat{x}$. The neural features directly estimate only the velocity for each DOF – weights in the top row of $\mathbf{B}$ were zeroed out. The state-space representation has a number of benefits including low computational overhead, straightforward analysis and implementation of smoothing, and the ability to adjust the neural features' influential strength directly.

The state-space representation of the system dynamics in $\mathbf{A}$ were set by hand to directly establish the amount of smoothing applied to the output. The weights applied to each neural feature in $\mathbf{B}$ were established based on a training sequence. The subject observed the MPL move through a series of predefined motions, and simultaneously imagined movement of his own arm in the same motions. A t-test over 10-fold R^2 values calculated between predicted and presumed kinematic trajectories was performed on the training dataset, and features with $p<0.1$ were used to parameterize the elements of $\mathbf{B}$.

After training, the subject was given unassisted control of the MPL endpoint position (EP). Features were calculated as the number of threshold crossings on each of 192 channels (96 recorded from the anterior intraparietal sulcus; 96 recorded from Brodmann's Area 5) in 50-msec intervals. On average, about 30-40 features were retained from the training sequence and used in the final parameterized decoder. In this preliminary context, the subject performed 42 brain-controlled reach-and-grasp trials in 2 sessions.

B. APL Autonomous Controller

The Autonomous Controller module is responsible for identifying the 6 DOF pose of manipulable objects within the MPL workspace and planning the limb trajectory and grasp pattern for the desired object.

Identification of the 6 DOF pose of the objects is handled by the machine vision sub-component. The primary sensor used is the Microsoft® Kinect (Redmond, WA) which contains an optical camera and an infrared-based depth sensor. To interface with the Kinect, several packages from the Robot Operating System (ROS) are used including the openni_camera and Point Cloud Library (PCL) packages. The openni_camera package interfaces directly with the hardware and publishes a 3D point cloud that is consumed by the PCL packages for post processing. Using the PCL libraries, a pass-through cube filter is applied to remove 3D points outside of the workspace of the MPL. The largest planar surface is then identified using a random sample consensus (RANSAC) algorithm. A Euclidean clustering algorithm then assigns a group of points on the planar surface to an object using a configurable distance threshold. Finally, objects are identified as either spherical or cylindrical through a RANSAC algorithm which also computes geometric properties of the object including the radius and height. The machine vision

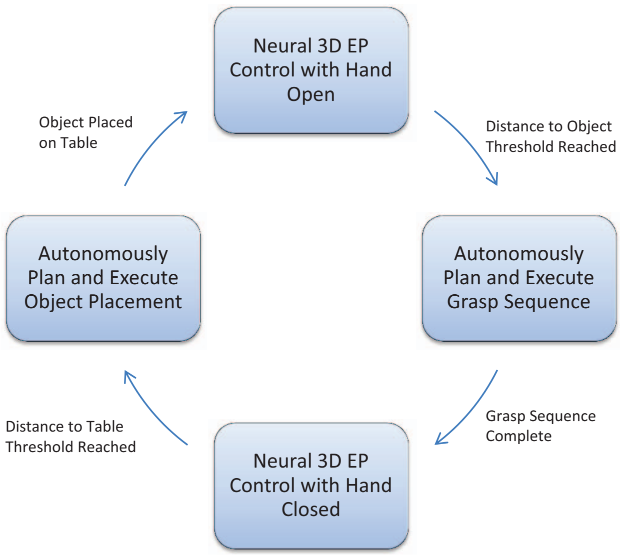

Fig. 2. State machine describing the Arbitrator.

sub-component publishes identified objects, the 6 DOF pose with respect to the camera as well as the geometric properties useful for computing the optimal approach and grasp strategy.

The arm motion planning and control within this hybrid control system is implemented as a three-level hierarchy consisting of task selection, arm path planning, and motion commanding. The user initiates a task using a high level command to select which task to perform. The path planning algorithm then autonomously calculates a set of waypoints in the arm joint space to perform the desired task starting at the current arm state. The hand and finger configurations are chosen based on the object type and orientation in order to align the hand with the object to be manipulated. Standard inverse kinematics algorithms are used to calculate the seven arm joints for each waypoint to achieve the desired hand position and orientation. The null space of the seven degree of freedom joint space is used to avoid mechanical joint limits and minimize the elbow height.

C. Arbitrator

The Arbitrator is implemented as a state machine (Fig. 2) and is used to blend autonomous control with neural decode control of the MPL. In its current form, the arbitrator allows the patient to control the 3D endpoint of the MPL using neural decode while monitoring the endpoint position of the MPL as well as the identified objects in the workspace determined by the machine vision sub-component. Once a Euclidean-based distance threshold between a potential object and the endpoint of the MPL is reached, the arbitrator switches control to the autonomous controller which computes a series of waypoints to maneuver the arm from the current location to the location of the desired object and automatically initiates the grasp sequence. Once the object is grasped by the MPL, 3D endpoint control is returned back to the patient to select a desired placement point of the object.

Fig. 3. Successful completion of a reach and grasp task.

Again, once a distance threshold between the endpoint of the MPL and the plane of the table is reached, the autonomous controller takes over and automatically computes the trajectory and grasp open sequence to place the object at the desired location.

III. Results

Utilizing the HARMONIE system, the spinal cord injury patient was able to successfully grasp a known spherical object (Fig. 3) and place it at a desired location on a table 97.6% of the time among the 42 trials performed over a testing period of two days. The mean time for completion of the grasp sequence was 42.2 seconds with a standard deviation of 20.1 seconds. The lone unsuccessful attempt was attributed to errors determining the true pose of the desired object due to occlusion by the arm. Future work will be focused on addressing this limitation.

IV. Discussion

In this paper, we described the utilization of the HARMONIE system to provide a collaborative framework that allows for shared control between direct neural decode and autonomous manipulation. While the results are only preliminary, the possibilities are promising. Using a single 3D endpoint neural decoder, an object recognition component and a arm trajectory planning module, the patient was able to accomplish a reach and grasp task that was previously difficult using direct neural control at that particular point in the training cycle. We envision that the HARMONIE system can be used to augment existing capabilities (i.e., add a grasp component to existing neural 3D EP control) that can allow for the execution of more complex tasks as well as to provide a training tool to better develop direct neural control. In the latter paradigm, the system can provide ground truth of object location and idealized trajectories for object manipulation. This idealized trajectory can be used as assistance and slowly tuned down as the neural control improves throughout the training cycle.

There are several directions in which we plan to continue this collaborative effort. Initially, we would like to add support for multiple neural decoders that are trained for a variety of subtasks. The objective of this is to develop building blocks that can be used for more complex activities. Also, we would like to develop a more sophisticated arbitrator that allows for better blending of direct neural control and autonomous manipulation instead of a binary switch between the two modes. Finally, we plan to scale the system to emphasize completion of activities of daily living. This involves developing a more robust object recognition system, developing a grasp planner that can determine optimal contact points for stable grasp given an arbitrary 3D shape of an object as well as utilizing sensors on the hand to confirm computed grasp points and force applied on the object.

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