Work Toward Real-Time Control of a Cortical Neural Prothesis

Robert E. Isaacs, D. J. Weber, and Aandrew B. Schwartz

***Abstract*—Implantable devices that interact directly with the human nervous system have been gaining acceptance in the field of medicine since the 1960's. More recently, as is noted by the FDA approval of a deep brain stimulator for movement disorders, interest has shifted toward direct communication with the central nervous system (CNS). Deep brain stimulation (DBS) can have a remarkable effect on the lives of those with certain types of disabilities such as Parkinson's disease, Essential Tremor, and dystonia. To correct for many of the motor impairments not treatable by DBS (e.g. quadriplegia), it would be desirable to extract from the CNS a control signal for movement. A direct interface with motor cortical neurons could provide an optimal signal for restoring movement. In order to accomplish this, a real-time conversion of simultaneously recorded neural activity to an online command for movement is required. A system has been established to isolate the cellular activity of a group of motor neurons and interpret their movement-related information with a minimal delay. The real-time interpretation of cortical activity on a millisecond time scale provides an integral first step in the development of a direct brain–computer interface (BCI).**

***Index Terms*—Brain–computer interface (BCI), cortical motor prosthesis, multi-unit recording, neural prosthesis.**

I. Introduction

Brain–computer interfaces (BCI's) primarily use noninvasive devices—electroencephalograph (EEG)-based methods—to interact with the central nervous system (CNS). Since the 1960's, with the development of the phrenic nerve stimulator, implantable devices that interact directly with the human nervous system have been widely accepted into the field of medicine. More recently, as is noted by the FDA approval of a deep brain stimulator for movement disorders, interest has shifted toward direct communication with the CNS. Research being conducted at Arizona State University, as a part of the NIH's Neural Prosthesis Program, is attempting to develop a cortical motor prosthesis. The goal is to design a system to record and analyze the activity of neurons in the motor cortex, and implement this to control a robotic arm. One potential benefit of this type of system would be a more accurate and versatile means of manipulating an artificial limb. We have demonstrated, with this initial step, the feasibility of this approach.

Neurons in the cerebral cortex typically display broad cosine tuning, and those in the motor cortex have been shown to be broadly tuned to the direction of hand movement [1]–[3]. These neurons will fire most rapidly for movements in their "preferred direction," and least when the motion of the hand is 180° away from it. Knowing the parameters that describe a given neuron's activity, a coarse estimation of the action of the hand can be made. When analyzed as a population, using a population vector or pattern recognition [4]–[7], a reconstruction with a high correlation (typically >0.9) to the true instantaneous velocity of the hand can be formed. The foundation of these works has been established using single-unit recording techniques; the same level of accuracy has yet to be proven in real-time using multi-unit recording. Technological advances are improving the ability to record and process the activity of multiple cells simultaneously. Concomitant with this, analytic techniques designed to extract information inherent in simultaneous recordings are providing an ability to reproduce the information encoded in the neural signal with fewer numbers of cells [8]–[10]. With this, the goal of online robotic control under direct cortical command draws nearer.

When a large number of neurons is present, a vector sum of weighted preferred directions, a population vector, should well describe the task being performed. With fewer cells, pattern recognition can provide a better estimation of the information present in the cortical signal [7]. A new method is being developed to use a principal component analysis (PCA) to find the patterns of coactivation that can identify the ensemble activity throughout each movement. Using the instantaneous firing rate of each identified neuron, the activity of different neurons can be compared to determine how they interrelate, and then the most deterministic relations can be used to recreate the motion of the hand. To do this, the cross-covariance of each neuron's activity with one another is

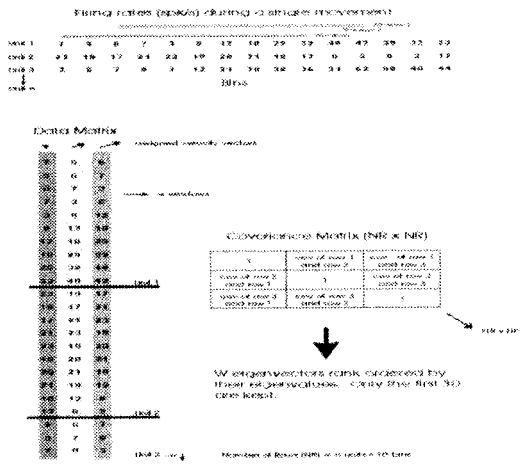

Fig. 1. Schematic diagram depicting the method used to derive interaction between cortical activity and hand motion.

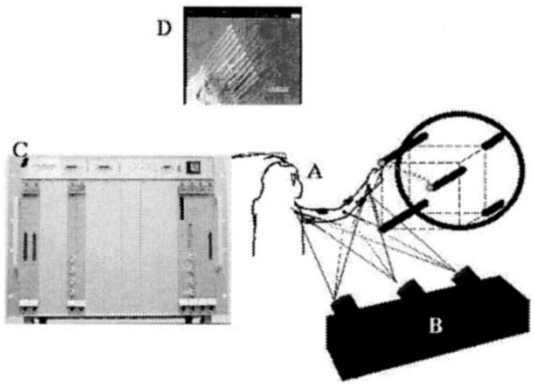

Fig. 2. Experimental setup (A) showing a rhesus monkey implanted with commercially available electrode arrays (D) performing a 3-D reaching task. An optical position sensor (B) tracks the path of the hand. The digital signal processing is performed by another commercially available device [(C) Plexon Multichannel Acquisition Processor, Dallas, TX]. The system. when run on a standard 430 MHz PC, can derive velocities at 125 Hz.

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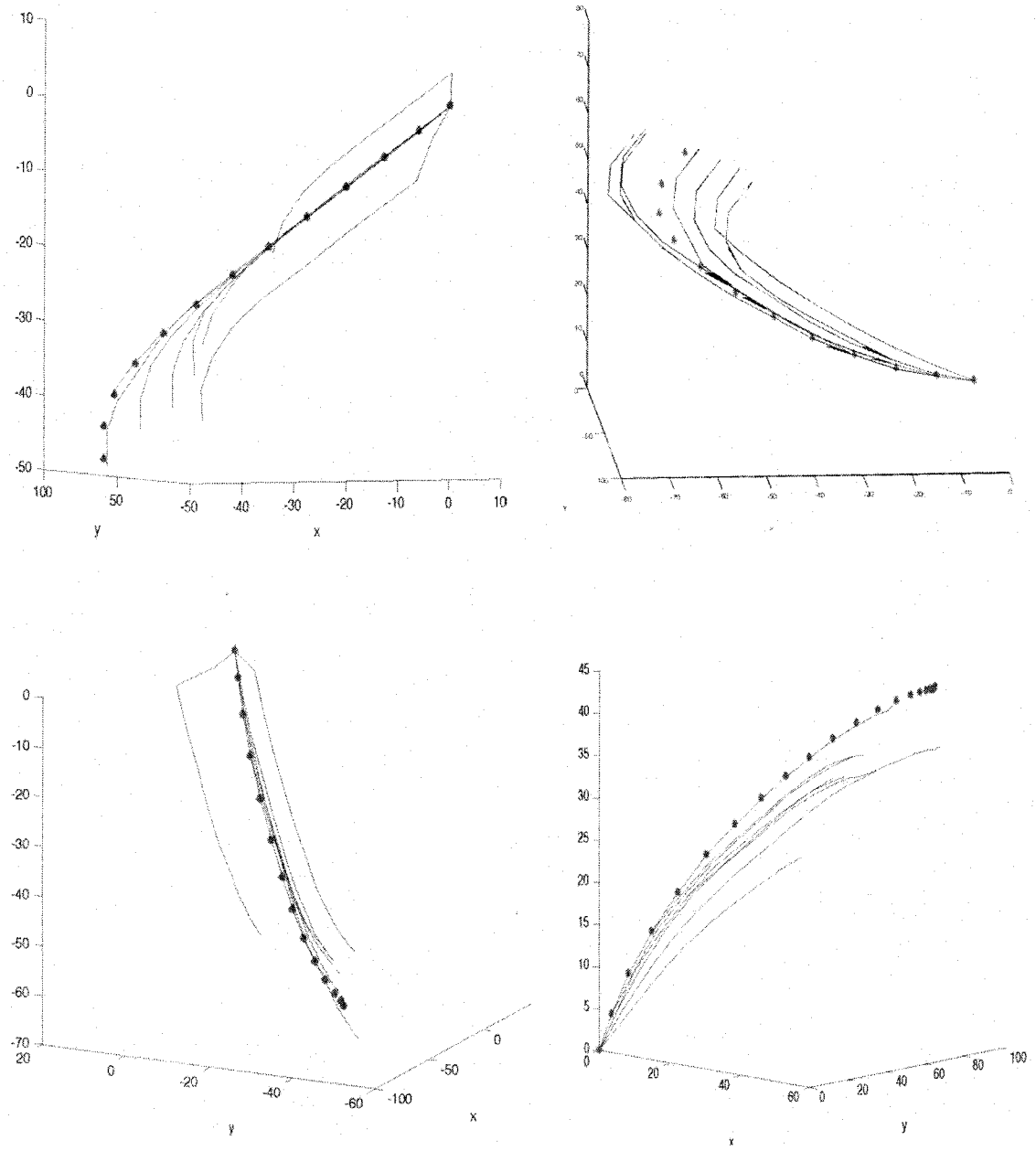

Fig. 3. Trajectories formed from the neural activity recorded on the last day of the experiment. For averaged movements (red dashed lines) to four of the eight targets, the blue lines represent the "neural trajectories" derived from simultaneously recorded neurons (from eight, single trials to each target). These display the potential consistency achievable with real-time neural interpretation.

calculated (see Fig. 1). After performing the PCA, the eigenvectors of this covariance matrix illustrate the patterns that best identify the group activity at any given moment. Once new cortical activity is related to known movements, an instantaneous velocity can be assigned.

Rhesus monkeys, which were implanted with chronic electrode arrays, were trained to perform a three-dimensional (3-D) center-out reaching task in a cubic workspace. All of the randomly obtained, task-related motor cortical neurons identified on the electrode arrays were included in the analysis. This resulted in normalized neural activity from over 30 simultaneously recorded neurons on any given day being grouped to find the temporal patterns of co-activation. A PCA was employed to define these patterns and reduce the data to a handful of unique identifiers. This constituted the calibration process. Every 20 ms, a sliding window of activity from all of the neurons was multiplied by the previously derived eigenvectors. This new set was compared with the training data in principal component space. The instantaneous velocity from the training data set to which the new data most closely matched was assigned for that moment in time. The velocity used was derived from trajectory data recorded during the training runs. No velocity was given if the pattern matched a point in time from the training data not associated with movement, and therefore a "start" and "stop" signal could be created. Adding these velocities tip-to-tail formed the trajectory.

The system used to access the neural activity and the chronic electrode arrays are available commercially. Recordings from each microwire in the electrode assembly (NB Labs, Denison, TX) are obtained using a JFET buffer amplifier that connects to a multichannel neural recording system (Plexon, Inc., Dallas, TX). The recording system provides channel-selectable, variable gains (up to 30 000X) and bandpass filtering (50–12 000 Hz), before sampling each channel

at 40 000 samples/s. Online spike discrimination is controlled interactively by the user and applies standard techniques of waveform template matching to isolate the neural activity from the lower background noise. The system saves spike waveforms and timestamps to the computer hard drive for all of the channels simultaneously, and can be accessed in real-time using client programs. This architecture has been extended to include online analysis of the cortical signal and will eventually be used to drive the robotic arm. Based on previous work [1]–[6], the system has been designed to derive velocity every 20 ms.

Using the system described above, client programs can be written which can make the necessary calculations to relate the neural activity to a control signal at 50 Hz. To run a robotic arm, an on-off signal, direction, and speed must be derived at every instant in time, and can be related back to the original arm movement for comparison. Over a two-month time period (83 640 time windows of activity analyzed), the system correctly predicted when the hand was in motion 81% of the time—with the most consistent errors occurring at the beginning and end of the movements. Overall, the median angle formed between the true and the derived movements was 22.3° for targets that were separated by a minimum of 60°. Individual whole movements (formed from the integration of the individual velocity vectors) ended closest to the correct target 68.5% of the time (1398 of 2040 trials), allowing the determination of the correct movement solely based on the endpoint. From the day with the most accurate results, 99 out of 200 neural trajectories landed within 3.0 cm of the true endpoint of the hand (located 10 cm from the center of the cube), and 87.5% of the trajectories were closest to the correct target, displaying the potential consistency that can be achieved with simultaneous neural recording. When both the hand was in motion and the system correctly determined a velocity for comparison, the median vector correlation between the true and the derived velocity was 0.82.

Research is being directed at the formation of a real-time control signal to drive a cortical motor prosthesis. Although the accuracy of the current system is limited, it does provide 3-D motion control, deriving direction, speed, and movement initiation and termination, from the firing activity of motor neurons. Using the system described above, the conversion from neuronal activity to movement on a millisecond time-scale is attainable. Sensory feedback allows for learning and cortical remodeling, which should improve the accuracy of the device through visual biofeedback. Once the animal is allowed to interact with the robotic arm as the task is being performed, we expect that the ability to control this device should improve. Therefore, further refinements in technology coupled with the addition of interaction with our device should aid us in accomplishing our goal of an implantable, intracortical BCI.

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Direct Control of a Computer from the Human Central Nervous System

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***Abstract*—We describe an invasive alternative to externally applied brain–computer interface (BCI) devices. This system requires implantation of a special electrode into the outer layers of the human neocortex. The recorded signals are transmitted to a nearby receiver and processed to drive a cursor on a computer monitor in front of the patient. Our present patient has learned to control the cursor for the production of synthetic speech and typing.**

***Index Terms*—Brain–computer interface (BCI), cortex, locked-in patients, Luman brain implantation, neurotrophic electrode.**

I. INTRODUCTION

Patients with locked-in syndrome are alert and cognitively intact, but cannot move or speak. They face a life-long challenge to communicate. They may use eye movements, blinks or remnants of muscle movements to indicate binary yes or no signals. To enhance communication for these patients several devices have been developed including EEG control of a computer. These systems can provide these patients with the ability to spell words as shown by Birbaumer *et al.* [6], and control of hand opening and closing as shown by Peckham and his colleagues [7]. In theory, however, none of these systems can produce the speed and precision that ought to be provided by directly recording neural activity from the human cortex.

Our approach is to implant the human neocortex using the Neurotrophic Electrode that uses trophic factors to encourage growth of neural tissue into the hollow electrode tip that contains two wires [1].

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