Toward Electrocorticographic Control of a Dexterous Upper Limb Prosthesis

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One of the most exciting and compelling areas of research and development is building brain–machine interfaces (BMIs) for controlling prosthetic limbs. Prosthetic limb technology is advancing rapidly, and the modular prosthetic limb (MPL) of the Johns Hopkins University/Applied Physics Laboratory (JHU/APL) permits actuation with 17 degrees of freedom in 26 articulating joints. There are many signals from the brain that can be leveraged, including the spiking rates of neurons in the cortex, electrocorticographic (ECoG) signals from the surface of the cortex, and electroencephalographic (EEG) signals from the scalp. Unlike microelectrodes that record spikes, ECoG does not penetrate the cortex and has a higher spatial specificity, signal-to-noise ratio, and bandwidth than EEG signals. We have implemented an ECoG-based system for controlling the MPL in the Johns Hopkins Hospital Epilepsy Monitoring Unit, where patients are implanted with ECoG electrode grids for clinical seizure mapping and asked to perform various recorded finger or grasp movements. We have shown that low-frequency local motor potentials (LMPs) and ECoG power in the high gamma frequency (70–150 Hz) range correlate well with grasping parameters, and they stand out as good candidate features for closed-loop control of the MPL.

An estimated number of 541,000 Americans were living with some form of upper limb loss in 2005, and this number is projected to more than double with an aging and growing population by 2050 [1].

Building Brain–Machine Interfaces

Loss of limb may occur congenitally or due to cancer, diseases of the vasculature, or trauma, including industrial or farming accidents and battlefield injuries. The recent wars in Iraq and Afghanistan have resulted in a large veteran population with substantial upper limb loss due to trauma. This population has inspired research in the development of advanced prosthetic limbs. An outstanding example has been the JHU/APL MPL [Figure 1(a)], developed under the sponsorship of Defense Advanced Research Project Agency (DARPA), which has 17 controllable degrees of freedom in 26 articulating joints [2]. This limb has actuators to control the shoulder, elbow, and wrist, in addition to the fingers and thumb, providing extensive dexterous capabilities. Such an advanced limb also poses a control problem. Traditional approaches have used myoelectric signals from the forelimb of transradial amputees. Another more recent approach has been the use of peripheral nerve reinnervation of the chest, using orphaned muscles as a biological amplifier for nerve signals to control a prosthetic limb [3].

Despite these well-accepted approaches, there is good reason to believe that it is possible to achieve direct neural control of prosthetics that is intuitive and adaptive, involving the subject's complete sensory, motor, and cognitive capabilities. This broad area of research, known as *BMI*, is attempting to leverage patients' still-functional brains for direct control of a machine, be it a prosthetic hand [4], a computer cursor [5], or a wheelchair [6]. The goal of BMI is to interject a machine into the anatomical pathways of the human nervous system to augment, alter, or replace a lost biological function. A basic schematic of a BMI is shown in Figure 1(b).

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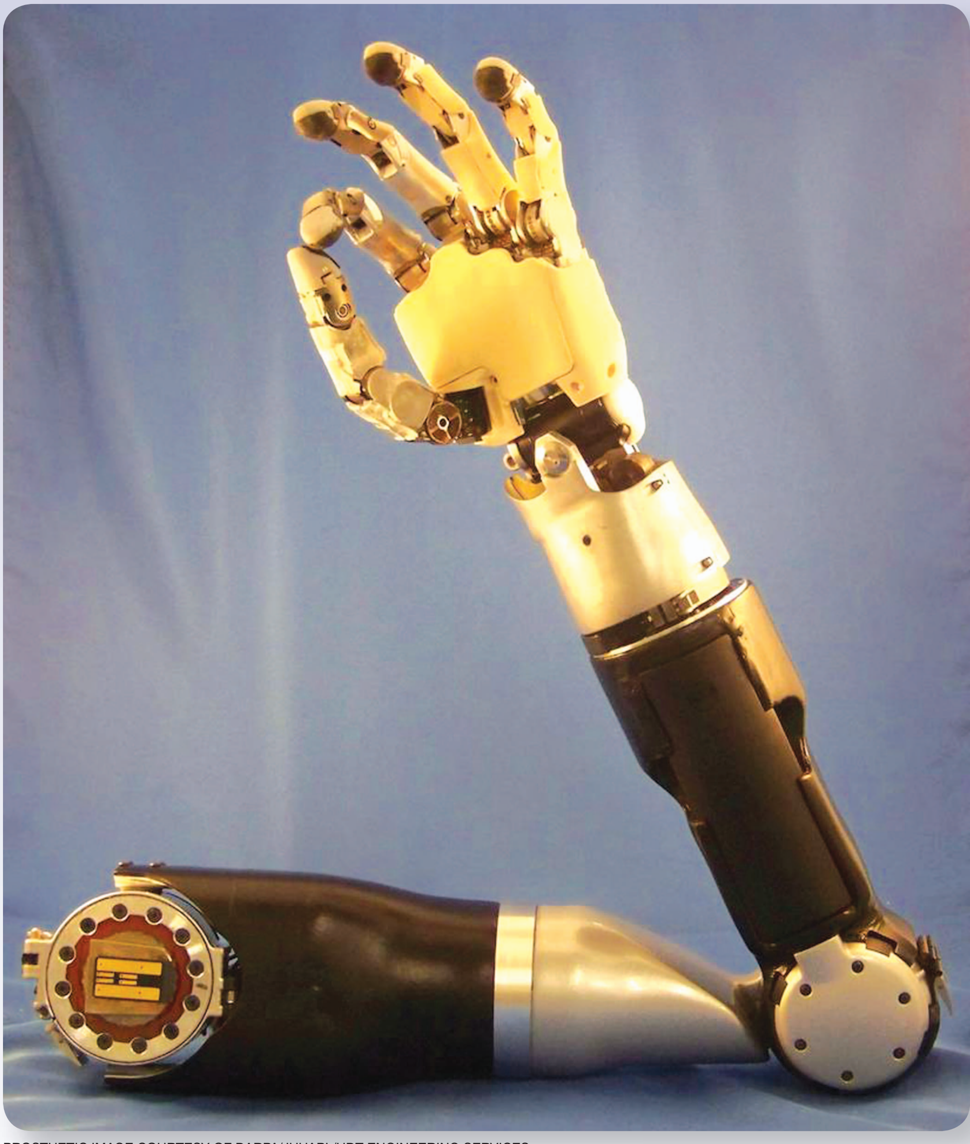

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and decoding of individual finger movements [9], slow grasping motions of the hand [10], and grasp type [4]. Two qualitatively different features of the ECoG signal are emerging from these studies. Power in the high gamma band (>70 Hz) has been established as a reliable index of cortical processing [11], [12], and the recently reported LMP [13] has been used for decoding slow grasping motions of the hand [10] and individual finger movements [9].

Methods

Neural Data Acquisition

The BMI community has explored many avenues of access to neural signals for BMI applications, but, traditionally, four modalities dominate: 1) EEG is the measure of neural potentials arising from the cortex from electrodes placed on the scalp, 2) ECoG is the measure of cortical potentials from the surface of the cortex, 3) local field potentials are the low-pass filtered (e.g., 200 Hz) electrical potentials recorded from cortex-penetrating microelectrodes, and 4) single or multiunit recordings to detect action potentials (or spikes) from neighboring neurons. Considering the potential strengths and weaknesses associated with these methods, ECoG occupies a unique middle ground among these technological tradeoffs. There have been a few pioneering efforts to use ECoG recording for BMI purposes. These include control of a cursor in one and two dimensions [7], [8]

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System Implementation

The system we have developed, and continue to refine, is designed to enable communication and synchronization of three distinct nodes. In general terms, these nodes are responsible for neural signal acquisition and processing, behavioral kinematic acquisition, and artificial limb actuation. Neural signal acquisition is accomplished using a Neuroscan SynAmps2 hardware that can be used to amplify either EEG or ECoG signals. For our ECoG experiments, neural signals are sampled at 1,000 Hz with a bandpass filter from 0.15 to 200 Hz. Neuroscan Scan software streams the raw neural data samples over transmission control protocol/Internet protocol (TCP/IP), where they are received by our custom MATLAB code and processed to extract signal features relevant to human motor movements. Raw neural signals are first rereferenced to a common average reference (CAR) in the time domain as a spatial filter to remove elements of the signal common to all channels. Time and frequency domain features are then extracted from the CAR-filtered channel data. Specifically, the signal power is extracted in five physiologically relevant frequency bands (i.e., μ band, 7–13 Hz; β band, 16–30 Hz; low γ band, 30–50 Hz; high γ band, 70–100 Hz and 100–150 Hz) using the fast Fourier transform and two amplitude time windows (i.e., 512 ms, 2,048 ms) using moving-average filters. These features are approximately

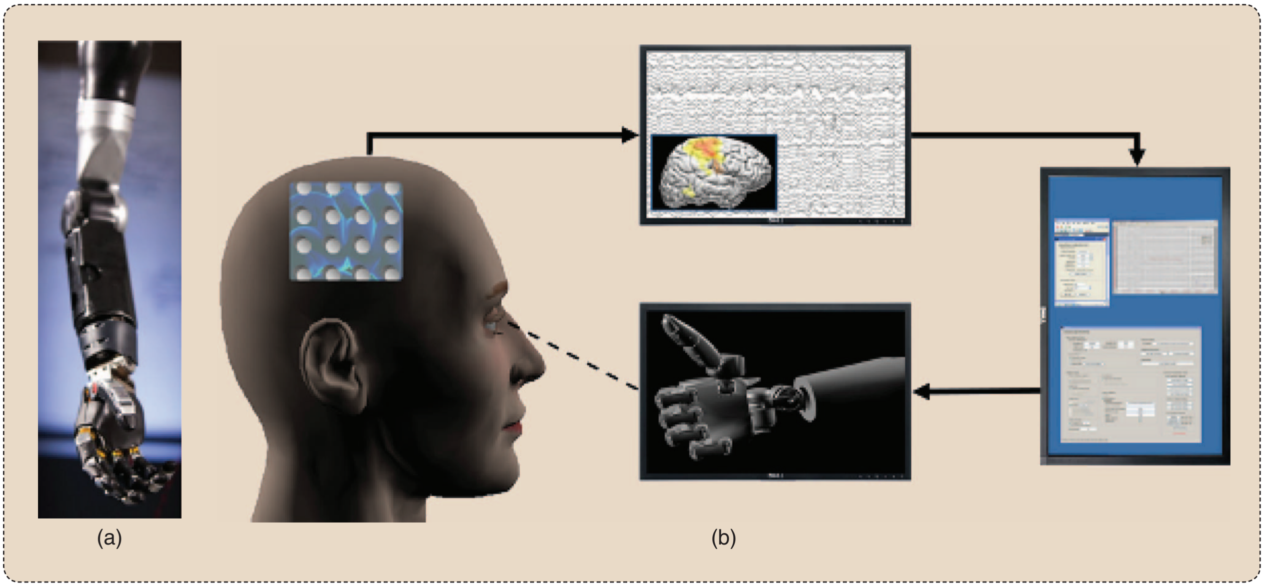

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FIGURE 1 JHU/APL MPL and an ECoG BMI schematic. (a) A photograph of the JHU/APL MPL. (b) The configuration depicted involves acquisition of the ECoG signals from electrodes placed on a human brain (left and top) and their computational analysis and modeling (right) to drive a prosthetic limb (bottom). The left and bottom figures have been adapted from screenshots of MSMS.

extracted every 40 ms and synchronized with the streaming behavioral kinematic data.

Behavioral kinematic data acquisition is accomplished using the Optotrak system and CyberGlove. Artificial limb actuation is achieved either in three-dimensional virtual or physical space. JHU/APL has previously reported and demonstrated MPL, a 27 degree of freedom prosthetic arm, complete with control of the shoulder, elbow, wrist, and fingers. This arm has been duplicated as a virtual model in the musculoskeletal modeling software (MSMS) simulation environment [14], which has been developed at the University of Southern California and is freely available online. The computational resources necessary to process the incoming neural and kinematic data are contained within a single eight-core Dell Workstation with 32-GB RAM, of which four are dedicated to MATLAB's parallel computing toolbox. A photograph of this environment, including a patient seated in his hospital room, is depicted in Figure 2(b).

ECoG electrode grids are predominantly implanted for clinical purposes in patients with uncontrollable epileptic seizures.

Results

We have used the system described to initiate research into ECoG-based control of a dexterous prosthetic limb. ECoG electrode grids are predominantly implanted for clinical purposes in patients with uncontrollable epileptic seizures [Figure 2(a)]. In a previously published study, our

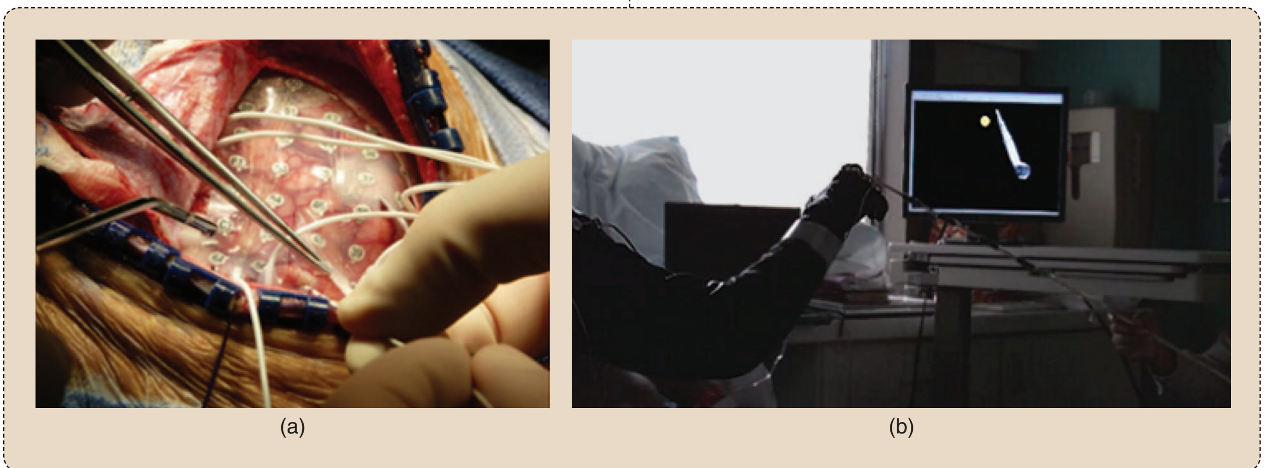

FIGURE 2 (a) An intraoperative photo of an ECoG grid being placed in a human patient. (b) A real object target is presented (from bottom right) as a cue to a patient (offscreen to the left for anonymity). The patient is pointing to the target, and his motions are being tracked by Optotrak markers on the shoulder and hand. The three-dimensional position of the patient's hand and cue are being displayed in the MSMS simulation environment. The virtual cue is yellow, indicating a successful trial.

laboratory discovered that the LMP recorded from subjects implanted with ECoG grids could be used to decode slow grasping motions of the hand with simple linear models. LMP signals with the highest correlation to the recorded kinematics were selected for inclusion in the decoding models. Peak decoding performance was achieved with as few as four electrodes in areas that can be intraoperatively identified as having motor involvement, meaning that these signals can be recorded from low-footprint ECoG grids implanted in known areas. These results are promising in the use of LMP signals for neuroprosthetic applications. The robustness of LMP as a phenomenon is validated by the high decoding accuracy across sessions.

The signal power is extracted in five physiologically relevant frequency bands.

In a more recent work from our laboratory, we investigated the neural signals responsible for the coordination of slightly more complex grasps [15]. Our study showed that frequency components in the high gamma band (70–100 Hz and 100–150 Hz) provide the best performance for decoding grasp aperture. Figure 3(a) shows the location of the implanted grid electrodes, with darkened electrodes corresponding to motor brain areas, as identified by electrocortical stimulation mapping (ESM). Figure 3(b) shows the spatial pattern of decoding accuracies obtained using 70–100 Hz power from single electrodes at various locations in the cortex. Again, the highest-performing electrodes appear to be concentrated over areas identified as having motor involvement before experimentation. Figure 3(c) demonstrates the correspondence between observed and decoded grasp aperture traces using the 20 features that best predict grasp aperture in each cross-validation training set.

Our results not only indicate that complex movements can be decoded from a patient's ECoG signal, but that both LMP (an amplitude feature) and high gamma band (a spectral feature) should be considered in decoding complex motor tasks. Although it is an area of active investigation, it is our hypothesis that the LMP, as a slower signal, encodes information about low velocity or repetitive movements fairly robustly, while the high gamma band may be more useful for decoding movements with higher degrees of complexity or more sudden onset.

Future Directions

We are making steady progress toward the dream of neural control of prosthetic limbs using a variety of means, but the journey is just beginning. A few major challenges in achieving ECoG-based control of dexterous prosthetic remain, including the following:

- improving the resolution of ECoG arrays (high-resolution ECoG with arrays of mini- and microelectrodes) may provide better localization to the areas of the cortex and is responsible for dexterous hand and finger movements
- maturation of decoding algorithms specifically suited to ECoG signals (signals in very low frequency as well as high gamma bands) may offer novel decoding capabilities and information

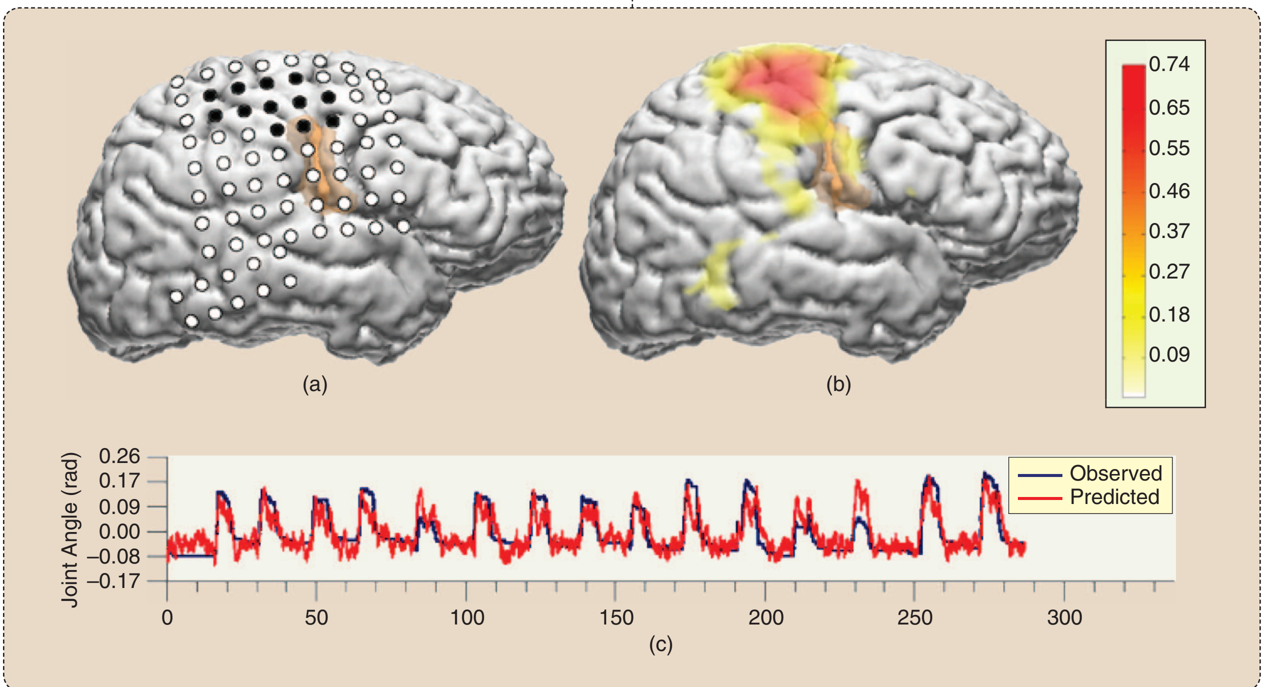

FIGURE 3 The spatial distribution of single feature decoding accuracy and example decoding trace with 20 features. (a) Circles denote implanted electrodes that were included in the analysis, while darkened electrodes indicate that motor behavior was elicited or interrupted during ESM. (b) Single-feature decoding accuracies: Pearson's correlation *r* between the observed and decoded traces. (c) The example traces show the fidelity of decoded grasp aperture to the observed grasp aperture. Predicted traces have been formed in fivefold cross-validation with linear models and trained with 20 distinct neural signal feature inputs. (Adapted and modified from [15].)

- provision of proprioceptive and touch feedback to the neuroprosthetic user (by stimulating intact peripheral nerves or directly stimulating the somatosensory cortex [16]) may greatly facilitate natural control of an artificial limb
- building fully implanted ECoG systems (long-term cortically controlled prosthetics) will need to be composed of electrodes, circuits, and telemetry interface to the limb while being fully implanted and powered
- ethical considerations in the selection of patients and implantation with regard to the potential risks and benefits to each individual patient.

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