

# Connecting Brains with Machines: The Neural Control of 2D Cursor Movement

Michael J. Black\* Elie Bienenstock†‡ John P. Donoghue† Mijail Serruya† Wei Wu‡ Yun Gao‡

\*Dept. of Computer Science, †Dept. of Neuroscience, ‡Division of Applied Mathematics  
Brown University, Providence, RI 02912

black@cs.brown.edu, elie@dam.brown.edu, john\_donoghue@brown.edu,  
mijail\_serruya@brown.edu, weiwu@cfm.brown.edu, gao@cfm.brown.edu

## Abstract

This paper presents a review of our neural prosthesis research program and provides a brief introduction to the field. We focus on four key problems: sensing, neural encoding, neural decoding, and interface design. We explore these problems and present our current solutions which have led to the direct cortical control of unconstrained 2D cursor movement.

## 1 Introduction: Neural Prostheses

Humans (and other animate creatures) survive in an environment by continually sensing and acting. Illness or injury however may impair or destroy the neural pathways connecting the brain with the external world. This includes auditory and visual impairments as well as motor impairment due to stroke, spinal cord injury, Amyotrophic Lateral Sclerosis, or Multiple Sclerosis. There are 250,000 cases of spinal cord injury alone in the United States of America with 11,000 new cases each year [1].

Research on neural prostheses seeks an engineering solution to restoring lost function by providing new, alternate, pathways which restore, to varying degrees, the ability to sense and act on the world. Neural prosthetic research takes many forms including auditory and visual prostheses, deep brain stimulation, and functional electrical stimulation. A full review is beyond the scope of this overview and here we focus on cortical control of external devices such as computer displays or robots. We review and summarize our research with implantable microelectrode arrays, neural decoding, and direct brain-machine interfaces.

Building a direct, artificial, connection between the brain and the world, requires answers to the following questions

1. What “signals” can we measure from the brain? From what regions? With what technology?
2. How is information represented (or *encoded*) in the brain?
3. What algorithms can we use to infer (or *decode*) the internal “state” of the brain?
4. How can we build practical interfaces that exploit the available technology?

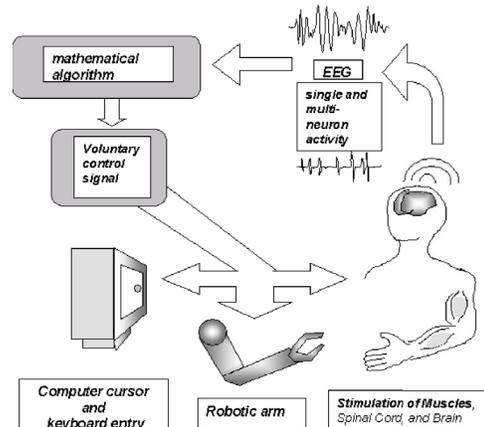


Figure 1: Brain-machine interface.

Our approach is summarized in Figure 1 and is outlined in the remainder of this paper. The following section addresses the problem of measuring signals from the brain using an array of chronically implanted microelectrodes. From this we record action potentials of individual neurons and then represent the neural signal using a rate code. We adopt a Bayesian formulation of the encoding/decoding problem and present a simple linear Gaussian model that reconstructs hand motion from neural activity in motor cortex. This reconstruction is sufficiently accurate to permit the control of unconstrained 2D cursor movement or simple robotic functions. We conclude with some speculative thoughts about future directions in the field.

## 2 Sensing Neural Activity

While there are a number of sensing technologies that can be used to observe neural activity directly or indirectly (e.g. fMRI, EEG, MEG, optical imaging), accurate, real-time, control of devices requires high spatial and temporal resolution. Consequently we exploit implanted recording devices which are quickly advancing towards clinical relevance and provide the spiking activity of individual cells. Our recordings are made using a chronically implanted microelectrode array illustrated in Figure 2. The array is implanted in the arm area of primary motor cortex in macaque monkeys; the

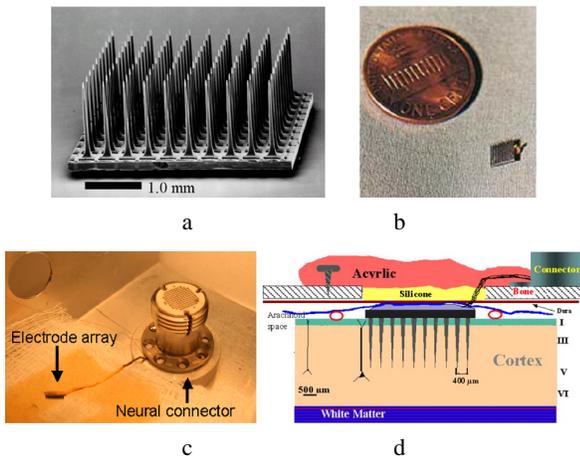


Figure 2: Implantable electrode array and connector (Bionic Technologies Inc.). (a) Electrode array. (b) Size in reference to a penny. (c) Array shown with percutaneous connector. (d) Sketch of the implanted array and connector.

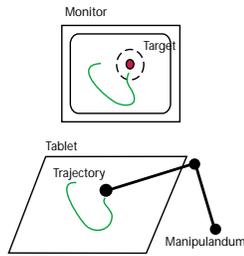


Figure 3: Experimental paradigm (see text).

area is easily accessible simplifying implantation. The device can be safely implanted (and explanted) with stable recordings being obtained over multiple years.

The firing rates of cells in this area of the brain have been shown to be related to the motion of the hand. The natural relationship between neural activity and motion of the body makes this an appropriate area to explore for continuous control of external devices.

Neural activity of multiple cells are recorded extracellularly, the neural signals are processed in real time, spikes are detected (and sorted if necessary), and the spike trains are converted to spike counts within non-overlapping time bins (typically 50-70ms). Current techniques permit recording from over one hundred cells simultaneously.

Neural recordings are made while a subject performs a variety of motor tasks. These typically involve viewing a feedback cursor on a computer monitor, the motion of which is controlled by the subject’s hand motion through a two-link manipulandum that is moved on a 2D tablet (Figure 3). The task considered here involves moving the cursor to “hit” randomly placed targets on the screen. Once a target is hit, it disappears and reappears in a new random location. The resulting hand motion is fairly natural and is

constrained only by the finite dimension of the 2D tablet.

Unlike paralyzed patients, current subjects have full mobility. This allows us to simultaneously record hand motion and neural activity and thus learn a model relating the two as described in the following section. Work by Kennedy *et al.* [5] with a single “neurotrophic electrode” suggests that various biofeedback training paradigms may be used in mapping neural activity to novel output devices even in patients who are paralyzed. See also recent work on cortical cursor control in restrained subjects [11].

### 3 Encoding and Decoding Neural Signals

An understanding of how the brain represents movement facilitates the design of appropriate decoding algorithms, forms the basis of our approach, and supports our two simultaneous goals. The clinical goal of providing a prosthesis is engineering oriented and does not necessarily require an understanding of neural coding. It has been suggested that simple models and algorithms may be sufficient for neural control of devices since the brain is a complex learning system which, with appropriate training, will learn new, and possibly arbitrary, mappings from neural activity to prosthetic output. We posit that exploiting the “natural” encoding strategies of the brain will lead to more intuitive interfaces which are easier to learn. This also supports our second goal of understanding how the brain represents and processes information. This encoding-based approach is in contrast to neural network methods that model the mapping from neural activity to movement as a “black box” [12].

It has been observed that cells in primary motor cortex fire maximally for a preferred hand motion direction,  $\theta$ , and exhibit roughly cosine-shaped tuning [4]. Moreover, the firing rate is roughly linearly related to hand speed,  $s$ , [9]. This cosine-tuning model is equivalent to a linear generative model of neural firing rates in terms of hand velocity:

$$\begin{aligned} z_{c,k} &= s_k (h_0 + h_x \sin(\theta_k) + h_y \cos(\theta_k)) \\ &= h_1 + h_x v_{k,x} + h_y v_{k,y} \end{aligned}$$

where  $z_{c,k}$  is the firing rate of a particular cell,  $c$ , at time instant  $k$ ,  $\theta_k$  is the direction of hand motion, and  $v_{k,x}$ ,  $v_{k,y}$  represent  $x$ ,  $y$  velocity respectively. The coefficients,  $h_1$ ,  $h_x$ ,  $h_y$ , can be fit from training data using linear regression.

Figure 4 shows the firing rates for a particular motor cortical neuron along with the best linear model fitting the data. Note that here the linear fit in  $v_x, v_y$  is plotted in terms of direction and speed illustrating the relationship between cosine tuning and linear models.

A model of velocity alone is not sufficient for accurate decoding of hand motion since control of 2D position would require the integration of noisy velocity estimates. Fortunately, simple linear models also relate hand position and acceleration (and possibly higher-order terms) to the firing rates of cells in motor cortex [14]. Figure 5 shows the cell’s

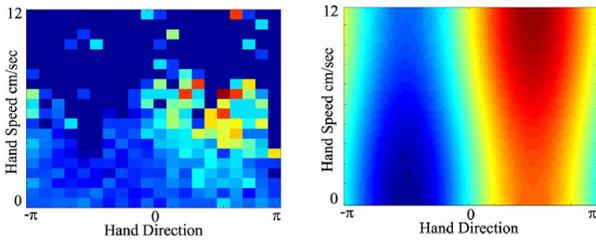


Figure 4: Left: firing rate of a cell as a function of hand direction and speed. Right: best linear model.

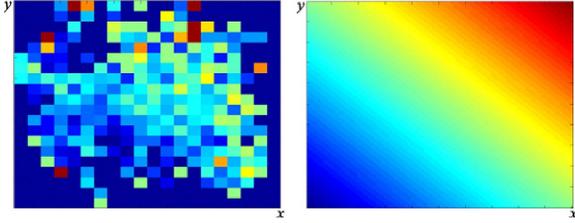


Figure 5: Firing rate for cell as a linear function of position. Left: raw firing rates. Right: best linear fit.

firing rate as a function of hand position along with the best fitting linear model. This linear relationship is exploited in neural decoding algorithms based on linear filtering [10].

This approximately linear encoding is captured by the following generative model

$$\mathbf{z}_k = \mathbf{H}\mathbf{x}_k + \mathbf{q}_k, \quad (1)$$

where  $\mathbf{x}_k = [x, y, v_x, v_y, a_x, a_y]^T$  represents the state of the system (i.e. the  $x$ -position,  $y$ -position,  $x$ -velocity,  $y$ -velocity,  $x$ -acceleration, and  $y$ -acceleration) at time bin  $k$ . The observations  $\mathbf{z}_k \in \mathbb{R}^C$  represent a  $C \times 1$  vector containing the firing rates of  $C$  cells at time bin  $k$ ; these observations are made zero-mean by subtracting the mean firing rates of each cell. The matrix  $\mathbf{H} \in \mathbb{R}^{C \times 6}$  linearly relates hand state to neural firing. For simplicity, we assume the noise in the observations is zero mean and normally distributed; i.e.  $\mathbf{q}_k \sim N(0, \mathbf{Q})$ ,  $\mathbf{Q} \in \mathbb{R}^{C \times C}$ . What is important here is that we model the full covariance matrix  $\mathbf{Q}$  relating the firing rates of the cells.

We also assume a linear model for the hand motion

$$\mathbf{x}_{k+1} = \mathbf{A}\mathbf{x}_k + \mathbf{w}_k, \quad (2)$$

where  $\mathbf{A} \in \mathbb{R}^{6 \times 6}$  models the evolution of the hand position over time. The noise term  $\mathbf{w}_k \sim N(0, \mathbf{W})$ ,  $\mathbf{W} \in \mathbb{R}^{6 \times 6}$  models our uncertainty in the state estimate.

With this linear formulation, a Kalman filter can be used to estimate the hand state [14]. This provides a simple, efficient, closed form, recursive Bayesian estimate. The approach has a sound probabilistic framework and it makes explicit our assumptions about the data (linearity and Gaussian noise). These assumptions can then be studied and

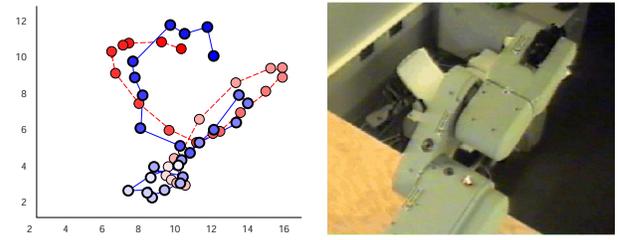


Figure 6: Neural control of devices. Left: reconstructed cursor trajectory compared with ground true. Right: robot arm control.

modified in a principled way. The Kalman filter requires a small amount of training data (less than 3 minutes in our experiments), provides estimates of hand state with little lag, and has proven more accurate than previous methods based on population vectors or fixed linear filters.

## 4 Interfaces

A brain-machine interface provides a direct link for transferring information between the brain and the external world. Here we focus only on the problem of output and, more specifically, on applications in which the brain controls some external device. There is a second meaning to the word “interface” that pertains to the design of computer systems. Research on brain-machine interfaces addresses both meanings of “interface”: the transfer of information and “user interface” design. See [13] for a review.

Our efforts above have focused on two-dimensional, continuous, control of a computer cursor. since this has broad applicability in interface design and can leverage existing computer interface technology (e.g. web browsing). Three dimensional control [11] has been demonstrated in simpler center-out movement tasks suggesting that our continuous control could be extended to 3D.

In open-loop experiments, we achieve relatively accurate reconstruction of 2D hand trajectories using the linear Gaussian model above (see [14] for experimental details). Figure 6 shows a short hand trajectory along with the trajectory reconstructed from the firing rates of 42 cells. These 2D reconstructions have also been used for open-loop control of a robot arm (Figure 6).

A neural prosthesis requires closed-loop control where the subject has (in our case) visual feedback of the cursor being controlled. In this case, input to the brain comes through an intact visual system while output is in the form of a brain-machine interface. Experiments with macaque monkeys show that they can effectively move a cursor under closed-loop neural control to hit targets presented at random on a computer monitor (Figure 3). Using a simple linear model relating neural firing and hand position, their performance on this task is similar to their performance using manual control [10].

Interface design for such devices is still in its infancy and additional functionality (such as “mouse” clicks) is needed for a clinically relevant device. The neural control of multiple control modes (continuous motion and discrete selection) is a topic of future research. While computer or robot interfaces may extend neural control to new domains, the ultimate “interface” for many patients may be to their own limbs using functional electrical stimulation [7].

## 5 Conclusions and Future Directions

Recent work by ourselves and others [10, 11, 12] has demonstrated the viability of controlling devices with signals obtained from neural implants in animal models. A great deal remains to be done including the development of fully implantable devices with telemetric output that would be safe for humans. We are also exploring other implantation areas (e.g. parietal reach region [3]) to study the interactions between brain regions and to explore “higher-level” neural control.

While the linear encoding models described here are suitable for neural control, we are exploring a variety of improvements. In particular, we have formulated generalized linear models, generalized additive models, and fully non-parametric models of neural firing that account for nonlinearities and non-Gaussian noise. These provide a better model of encoding at the expense of more complex decoding methods based on particle filtering [6]. Additionally, we are currently exploring the relationship between arm joint angles and neural firing.

Our generative models can be used to detect changes in the tuning properties of a population of cells due to adaptation or plasticity. We are developing adaptive decoding methods that can cope with such changes and in future work we will systematically explore issues of plasticity.

In addition to computer-based interfaces, we are exploring other output modalities. In particular, our decoding of smooth 2D trajectories suggests the possibility of using neural signals for telerobotics though many problems remain to be solved. We believe effective neural robot control will require a semi-autonomous platform with obstacle avoidance capabilities.

Beyond smooth motions, we are exploring the recognition of more complex, compositional motions or “gestures”. Recognition of such discrete gestures could be mapped to “commands,” letters, or words.

In closing, it is worth noting that neural prostheses provide only one possible avenue for the treatment of motor impairment and they complement research on, for example, spinal cord regeneration. While our current clinical goals focus on restoring lost function, it is worth noting that neural prostheses provide the opportunity for engineering new output modalities and new paradigms for brain-machine interaction.

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