Proceedings of the 1st International IEEE EMBS
Conference on Neural Engineering
Capri Island, Italy • March 20-22, 2003

Brain-Machine Interfaces in Rat Motor Cortex: Implications of Adaptive Decoding Algorithms

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Abstract-**Construction of a direct brain-machine interface (BMI) for neuroprosthetic purposes is at the forefront of many current neural engineering thrusts. Due to recent breakthroughs in device technology and implantation techniques, a basic framework is now sufficiently developed to allow design of systems level interface strategies producing robust, scalable BMIs that adapt quickly to optimize information transfer at the interface. It has been postulated that knowledge of the underlying neural coding is mandatory for further BMI development. In this preliminary report we use an adaptive algorithm requiring limited knowledge of the underlying neural coding to allow naïve rats implanted with Michigan silicon microelectrode arrays in motor cortex to perform a tone discrimination task via differential modulation of the recorded signals. One subject was able to perform the task consistently above chance, despite minor daily fluctuations in recording populations and signal quality. The brain rapidly changed response strategies to facilitate performance of the task, and the algorithm subsequently adapted to accommodate improved BMI operation.**

Keywords **- extracellular recording, neuroprosthetics, silicon microelectrodes, brain-machine interface, motor cortex, operant conditioning**

I. INTRODUCTION

The construction and characterization of a chronic brain-machine interface (BMI) is one of the principal challenges in modern neural engineering. Indirect BMIs using brain-derived signals acquired non-invasively through EEG techniques have produced benchmark information transfer rates of 10-25 bits/min [1]. However, due to the spatial and temporal signal degradation produced by the meninges, cranium and scalp, indirect BMIs will possess reduced information transfer rates compared to their direct BMI contemporaries. Direct BMIs interface with the neuronal elements in the brain using signals from single neurons or small groups of neurons. Consequently, the signals possess a much greater potential information transfer rate than through EEG recording. Though, previously limited by technological constraints, recent advances in devices and techniques have rendered direct BMIs a viable choice for a BMI system designer.

Optimal engineering of a BMI system involves consideration of the brain as a dynamic, adaptive controller. Therefore, BMI systems providing adequate feedback information to the brain will be the most successful. Several classical reports emphasize the idea of closed-loop feedback to the brain [2, 3], and a recently renewed interest in the field has provided additional demonstrations of closed-loop feedback improving direct BMI performance [4-8]. The power and time-scale of the brain's adaptation in these examples is remarkable. Some investigators have suggested that a primary focus for BMI development should be in understanding the neural coding principles employed by the interfaced neural tissue [9]; however, this point-of-view may underestimate the brain as a controller. Additionally, it may prove counter-productive under circumstances where the interfaced neurons are not involved in the operant task. If the brain does adapt as dynamically as the above reports suggest, quantifying the neural coding in an open-loop setting may be pointless, since the coding strategies will change in the closed-loop case.

Here we report preliminary results from a BMI system in the rat motor cortex. The subject is required to perform an auditory discrimination task, responding via neuronal action potentials recorded on a chronically implanted Michigan silicon microelectrode array. The BMI system is robust, adapting to fluctuating signal quality and content in time. Additionally, the BMI system is designed to adapt on a slow time-scale, so as to not to conflict with the rapidly adapting brain. The result is little decrease in subject performance after perturbation in a signal quality or content.

II. METHODOLOGY

A. Device and Surgical Implantation

Three male Sprague-Dawley rats (250g - 300g) were chronically implanted with Michigan silicon microelectrode arrays. Microelectrode array and surgical details are described elsewhere [10]. Briefly, electrode geometry consisted of four 50 µm wide thin-film silicon shanks separated by 200 µm. Each shank had four sites separated by 200 µm. The electrodes were implanted into the forelimb area of the rat's primary motor cortex with coordinates of AP: +3.0um, ML: 2.5um, as described by Sanes et. al [11]. Upon implantation the crainiotomy was closed via ALGEL® and dental acrylic (Co-Oral-Ite Dental Mfg. Co.), and the animal was allowed 48 hours to recover from surgery. All procedures complied with the United States Department of Agriculture guidelines for the care and use of laboratory animals and were approved by the University of Michigan Animal Care and Use Committee.

B. Behavioral Task

Initially, the rats were food deprived to 80% of their free-feeding weight. They were subsequently trained in a

This work was supported by DARPA contract number N66001-02-8059 as part of the BMI program.

two-choice, go/no-go discrimination task. Subjects responded in standard operant conditioning behavioral boxes (Med Associates, St. Albans, VT) located within an anechoic chamber. Subjects were positively reinforced for correct responses via single food pellets (P.J. Noyes, 45 mg rodent diet I, Lancaster, NH) delivered in a 5 cm by 5 cm tray located at the base of one wall of the cage. A 28 V house light at the rear of the box was used for cage illumination. The behavioral apparatus was controlled and monitored by in-house software developed using Matlab (Mathworks, Natick, MA), running on a PC interfaced with digital input-output hardware (System III, Tucker-Davis Technologies, Gainesville, FL). This equipment was also used to generate all auditory stimuli used in the experiment. The auditory stimuli were delivered via a speaker (Yamaha NS-10M Studio, Yamaha Corporation, Buena Park, CA) located 1 m directly above the test box. The system delivered a near-flat frequency response between 500 Hz and 32 kHz. The system was calibrated to a position at the food delivery tray; although calibration measurements indicated that the test box approximated a free field.

During each experimental session neural electrophysiological data from the 16 electrode channels sampled at 40 kHz were simultaneously amplified and bandpass filtered (450 – 5000 Hz) on a Multi-Neuron Acquisition Processor (MNAP; Plexon Inc, Denison, TX). Manual neuron sorting was conducted prior to each experimental session. Neural firing times were uploaded via the internet to the apparatus-controlling Matlab program.

Each experimental session consisted of 300 trials. Trials consisted of a 10 second inter-trial interval, a 1 second stimulus, and a response window of up to 4.5 seconds. For each trial one of two set points was presented. The set points were auditory tones of either 1 kHz or 10 kHz at 70 dB SPL. Neural firing modulation across the microelectrode array was monitored to determine the response to the given set point as described below. Based on the response, each trial was termed either "correct", "wrong" or "late". Correct and wrong responses terminated the response window, and a correct response was reinforced with a single food pellet. Wrong responses were not reinforced. Late responses occurred if no response was given within the 4.5 sec response window; these trials were also not reinforced. For each experimental session the correct, wrong, and late percentages were calculated.

In order to determine the neural firing rate modulation, a weighted average of the response firing rate relative to a baseline firing rate was calculated. The baseline firing rate for each microelectrode channel was determined by binning the neural data during last 1.8 seconds of the inter-trial interval into 90 ms bins and calculating an average firing rate and standard deviation. The response window data was binned into 90 ms bins, and a 450 ms window, sliding in 90 ms increments, was used to calculate an average response firing rate for each channel. The baseline firing rate average for each channel was then subtracted from the response window average. This channel modulation data was multiplied by two sets of channel weights. The weighted modulation data was then compared channel by channel to an adaptive threshold and averaged across each set. The adaptive threshold was based on the baseline firing rate standard deviation as described below. The output of the algorithm for each 90 ms time step in the response window was two numbers representing the neural modulation for each response state.

In each trial the two response states were tested via two unique sets of channel weights corresponding to the two possible trial set points. Initially, the channel weights were chosen at random. Subsequently, an adaptive algorithm calculated the optimal channel weights for each of the set points. For a correct answer to the given set point, the ratio of the response firing rate to the baseline firing rate was calculated and tabulated for that set point's weights. The weights for that set point were then modified based on the average criterion-baseline firing ratio of the last 10 correct trials for that set point. Each weight converged to the channel's percent modulation for each set point such that: no firing rate modulation resulted in a zero weight, increased modulation resulted in a positive weight, and a decreased modulation resulted in a negative weight. Set point weights were carried over from day to day.

For each sliding increment of the response window an adaptive threshold above the baseline firing rate was calculated. A response for a trial was established if only one response state exceeded threshold. If both exceeded the threshold the response was considered null and the window continued sliding. The initial threshold was two standard deviations above the baseline firing rate, but on all experimental days after day 1, the threshold was continuously adapted to converge the number of answered (correct or wrong) trials to 80% of the total trials (20% late).

III. Results

A. Behavioral Data

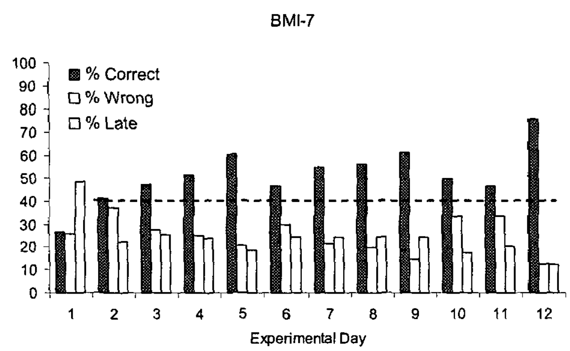

Fig 1. Daily behavioral results of two tone discrimination using neural responses across the microelectrode array from subject BMI-7. For each daily session, percent correct, percent wrong and percent late are plotted.

One subject was able to discriminate the auditory stimuli above chance via channel responses on the microelectrode array. Chance was calculated as 50% of the non-late trials, owing to the forced-choice nature of the paradigm. Due to the threshold adaptation, chance was 40% on experiments conducted after day one. This was also determined experimentally via controls involving a naïve subject and by removing the rewards from the trained subject. These controls resulted in 39% and 33% correct respectively.

For each experimental session the percent correct, wrong and late were calculated. The results from 12 sessions of daily experiments are shown for subject BMI-7 in Fig 1. The subject was able to discriminate the auditory cues above chance after three experimental sessions. A central result is the sharp increase in the discriminability, or the ratio of correct to wrong trials, after day 2. Additionally, regardless of variability in recording quality or unit selection within a session or from session to session, the subject was able to maintain a correct response rate above chance from day 3 to day 12.

B. Neural Recordings

Data from all 16 electrode channels were examined for stimulus-onset modulation. To evaluate the different response states of the subject, peri-stimulus time histograms (PSTHs) were constructed for both of the set points. PSTH data across four electrode channels for three experimental days are shown as Fig. 2. The PSTHs for set point 1 (1 kHz) modulation are shown in blue and the red curves indicate the PSTHs for set point 2 (10 kHz). The four channels displayed exhibited the most modulation across the 16 channel electrode array. Therefore, they also converged to the highest absolute valued weights in the adaptation algorithm.

Interestingly, the brain adopts the same response strategy from day 8 to day 9, in fact, becoming more "tuned" as indicated by the ordinate increases on day 9. Between days 9 and 10, the channel displaying the most modulation on previous days (channel 4) lost the activity that had been recorded earlier. Consequently, on day 10, channel

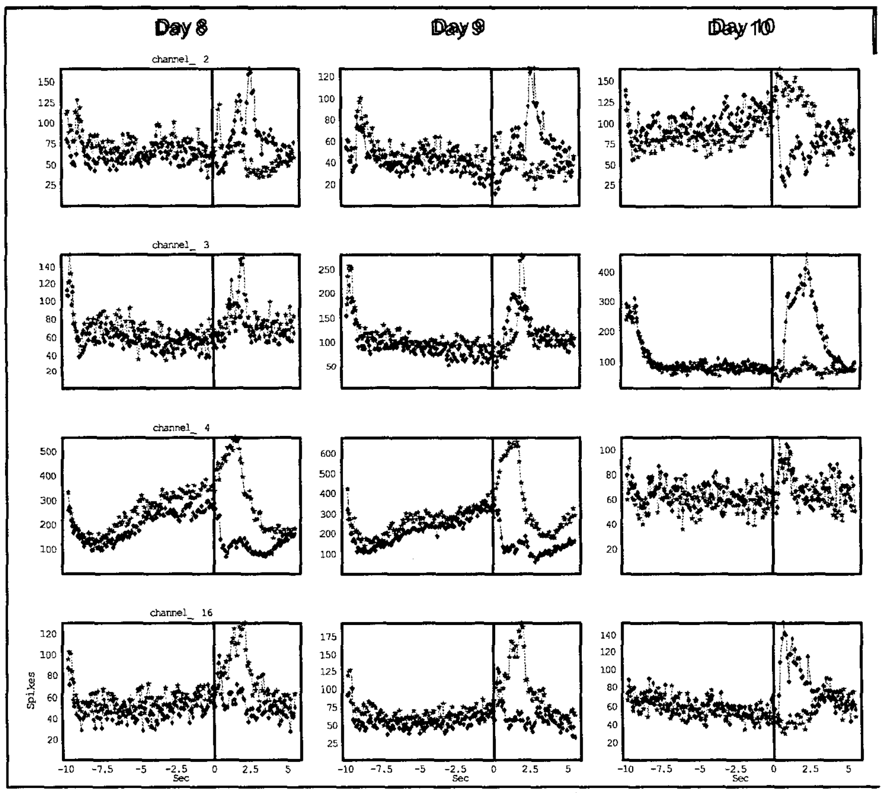

Fig. 2. Peri-stimulus time histrograms (PSTHs) of four channels across three experimental sessions. Each graph shows the channel responses to all set point 1 presentations (blue diamonds) and set point 2 presentations (red stars). Set points one and two were pure tone bursts at 1 kHz and 10 kHz respectively. The zero second point on the abscissa is the time of stimulus onset, and the stimulus lasted 1 sec. The abscissa displays the entire time course of a trial, including the 10 sec inter-trial interval, the 1 sec stimulus, and the 4.5 sec response window. On day 10, the previous day's unit activity on channel 4 was absent; the ensuing PSTH reflected a large reduction in stimulus modulation, and no differential modulation between set points. As a result, the response strategy exhibited on the other three channels changed significantly.

4 exhibits little modulation to either set point, and the other three channels now exhibit an entirely different response strategy. This strategy was accommodated by the adaptive algorithm, and the performance, as shown in Fig. 2 is only mildly hindered due to the initial learning curve of both the subject and the algorithm.

IV. DISCUSSION

An optimal BMI system will putatively be: dynamic, robust, scaleable and modular. As BMI system design progresses, metrics of the information transfer capability from various systems to and from the brain must be obtained relative to these system properties. In this study we begin to investigate some of these properties through implementation of a BMI in rat motor cortex, testing the information transfer from the brain.

This BMI provides dynamic, system level, software based adaptation that allows rapid optimization of performance. BMI system adaptation on the order of hours to minutes has been shown to be important for subject performance of a neural control task. The BMI in this experiment was robust to the degree that even with daily neuronal population changes, the algorithm-brain system allows for performance above chance. Several investigators have demonstrated similar degrees of adaptation and robustness [4-6]. Using a systems-based design approach, this system tends to be both scaleable and modular. As new tasks or technologies are encountered, individual components within the block diagram can be modified or replaced.

A unique property of the presented BMI system is *that it* requires no prior tuning properties knowledge of the recorded neurons for adequate system performance. For the initial trial, random weights are assigned to each channel for each set point. Subsequently, the system adapts based on stereotyped responses across the microelectrode array to allow subject responses. This system design strategy may prove important in implementation of neural prosthetic systems for disabled humans, in which neural tuning properties will be unattainable.

V. CONCLUSION

Design of a direct BMI system is one of the primary challenges in modern neural engineering. A fundamental question encountered in BMI system design is the degree of "tuning" built into the model. This system provides initial evidence that an intra-cortical BMI with limited prior knowledge of the neural coding mechanisms of the interfaced neural tissue can effectively provide above-chance performance in an auditory tone discrimination paradigm. The BMI system demonstrated here allows the brain to converge to preferred output states, subsequently adapting to accommodate these response strategies.

ACKNOWLEDGMENT

The authors would like to thank Jamie Hetke and Dr. Justin Williams for their assistance. Probes were provided by the Center for Neural Communication Technology sponsored by NIH NCRR grant P41-RR09754.

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