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Neural Adaptation of Epidural Electrocorticographic (EECoG) Signals during Closed-loop Brain Computer Interface (BCI) Tasks

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Abstract— **Invasive BCI studies have classically relied on actual or imagined movements to train their neural decoding algorithms. In this study, non-human primates were required to perform a 2D BCI task using epidural microECoG recordings. The decoding weights and cortical locations of the electrodes used for control were randomly chosen and fixed for a series of daily recording sessions for five days. Over a period of one week, the subjects learned to accurately control a 2D computer cursor through neural adaptation of microECoG signals over "cortical control columns" having diameters on the order of a few mm. These results suggest that the spatial resolution of microECoG recordings can be increased via neural plasticity.**

I. Introduction

At the current time, there remain several limitations to forming an effective neuroprothesis for voluntary motor control. Brain controlled interfaces (BCI) are always faced with the trade-off between invasiveness and robustness of signal. At the one extreme, electroencephalography (EEG) relies on signals from noninvasive electrodes placed directly on the scalp. While one and two-dimensional control has been demonstrated with EEG [1, 2], the poorer accuracy and learning rates have limited its efficacy compared to other methods of BCI. In contrast, intracortical electrodes have been demonstrated as an effective source for a BCI [3, 4]. However, these types of recordings require complicated, highly invasive surgeries. Additionally, the quality of these recordings tends to decay over time as electrodes become encapsulated by the immunologically reactive tissue.

An intermediate control signal modality, known as subdural electrocorticography (ECoG), has also been proposed as a possible signal source for a brain-computer interface. Previously, event-related potential (ERP) changes of the ECoG signal have been used to identify the onset and timing of various motor actions on individual trials [5]. Additionally, it has been demonstrated that event-related power changes recorded using ECoG can be used for mapping somatotopic areas of sensorimotor cortex associated with visually cued movements of different body parts [6]. A Fourier transform or Fourier-like algorithm is performed over given time windows during both a given task as well as at rest. Using this analysis to estimate the power at different frequencies of the signal for the given epochs of data, it is possible to identify different frequency components that increase or decrease in power during the task compared to rest. Historically, two bands that have been specifically identified were the alpha (8-13 Hz) and beta (15-25 Hz) bands which tended to show a decrease in power with the onset of motor movement or imagery [6].

Our lab demonstrated that human ECoG could be used for real time, closed-loop control using motor imagery tasks as the training paradigm [7]. For this control, power levels in 3 Hz bands ranging from 10-200 Hz were used. Patients learned to control a computer cursor in minutes, unlike months or years as is typically required in EEG [2, 8]. By simply placing electrodes on the surface of the brain below the skull and dura, high frequency signal components, not detectable on the scalp via EEG, were available to be used for control. Additionally, analysis of the ECoG signals following the experiment revealed that higher frequencies up to 180 Hz showed differences between movement and rest as well as between different joystick movement directions.

At the present time, there remain many questions about how to best optimize an ECoG brain-computer interface. Specifically, it is still uncertain what frequency bands and power spectrum estimation algorithms are best suited for control. Choosing optimal control parameters is complicated by the cortical changes that occur once brain signals are directly used for a closed-loop BCI. The signal changes and decoding that best predict motor movements during open-loop recordings may not be the best once the subject switches to closed-loop brain control where the cortical signals directly control the cursor. This paper examines the neural signals and the adaptation that occurs during closed-loop ECoG BCI tasks to gain insight into improving future BCI performance.

II. Data Analysis

Our lab has trained monkeys to perform two-dimensional closed-loop control of a cursor with EECoG. In these experiments, no open-loop training was done to identify event-related signals. Instead, arbitrary recording sites in motor cortex (M1) were assigned to control the cursor using the power within the frequency range from 65-100 Hz. The 65-100 Hz frequency band was chosen because previous amplitude increases in this high gamma band had been

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observed in M1 during arm movements compared to rest. Over the course of five recording days, the subject was able to achieve control of a cursor to successfully perform center-out reaching tasks as well as circle drawing tasks.

Two recording sites spaced one cm apart from each other were used to control the cursor velocity. One site was assigned to control the horizontal velocity where an increase in amplitude between 65-100 Hz caused the cursor to move to the right while a decrease caused the cursor to move to the left. Likewise, the other recording site amplitude between 65-100 Hz controlled the vertical cursor velocity.

The first task was a center-out reaching task where the subject controlled the cursor to acquire a center target and then move to one of four targets at the periphery. The second task was a drawing task where the subject controlled the cursor to trace around a circle in either the clockwise or counterclockwise direction. For the center-out task, the subject was able to complete 40 movements in approximately six minutes. Additionally, the monkey was able to complete 30 circle drawings in approximately seven minutes.

Following the completion of this closed-loop EECoG experiment, post hoc analysis of the data was done to examine and give insight into how closed loop control could be improved in the future. Two different types of analysis were conducted. First, for successful two-dimensional control, there must be two independent control signals. In the present experiments, these two degrees of freedom were obtained by using two different recording sites located approximately one cm apart. The circle drawing data was analyzed to determine how independent these two signals were. Additionally, for a successful brain computer interface, the signal should be optimized for optimal time response properties while maximizing the amount of signal to noise. To examine different potential control properties, the center-out data was analyzed using different control parameters than those used for the actual experiment.

A. Circle Drawing Task

The circle drawing task provides an excellent way to analyze how well a subject is able to independently control two degrees of freedom. In order to draw a perfect circle using standard x and y Cartesian coordinates for control, it is necessary for the velocity control signals to be both positive, both negative, and opposite each other such that the cursor can be directed to move in all directions. Fig. 1 shows the average path of the cursor for 90 circles drawn on the third day of recording. While performing the task, the left and upward directions were coded for by increases in power at their respective recording sites. Therefore, since the cursor path tends to be more of an ellipse along the upper-left to lower-right diagonal, it appears that the two recording sites were correlated such that both sites tended to be higher or lower power rather than one being high and the other being low.

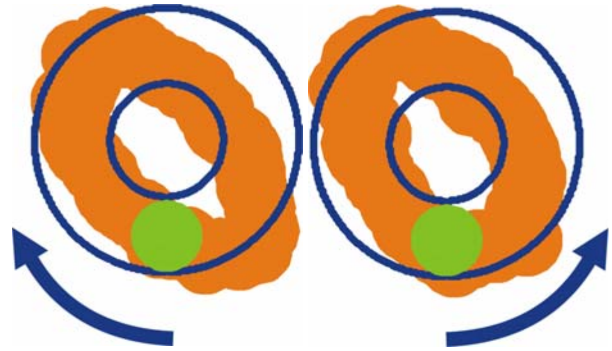

Figure 1 - The average cursor trajectory for counter-clockwise and clockwise circles with closed-loop control. The large green circle represents the start and end location for the trial.

In order for the monkey to improve his performance in the circle drawing task, it is necessary to decorrelate the two signals being used for control. This decorrelation could be done either indiscriminately across all frequencies or only within the frequency band being used for control. To examine what was occurring during the experiment, power spectrum analysis was performed on the two recorded signals in 300 ms time bins and 3 Hz frequency bins. The correlation between the powers at each given frequency for the two different channels was then calculated for all points in time. Fig. 2 shows the resulting correlations for the five days of recordings. This clearly shows that the correlation between the recording sites dropped between 65-100 Hz. It should also be noted that it also appears that the signals became decorrelated at higher frequencies and also were less correlated to begin with.

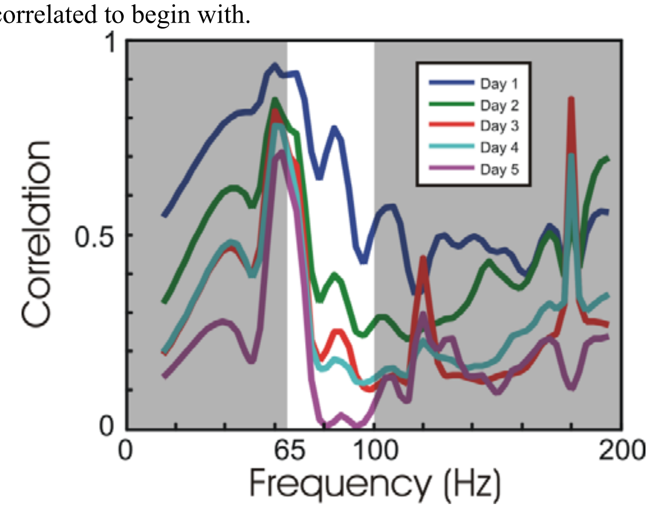

Figure 2. The correlation between the two recording sites used for horizontal and vertical control at various frequencies across five days of recording.

B. Center Out Task

The center out task is based on a given desired goal rather than a desired path. Therefore, it is easier to determine the optimal movement direction at any point in time. It has been shown that for unconstrained point-to-point arm reaching tasks, subjects tend to follow an approximately straight line [9]. Additionally, when the same force field is used to significantly alter the dynamics of the task for multiple trials, subjects tend to adapt to converge back to similar straight line trajectories [10]. Therefore, our closed-loop control data was analyzed using the assumption that a straight line between the cursor and the target was the optimal trajectory. This allows us to go back and compare various decoding schemes based on the recorded signals to examine how well their decoded direction fits the desired direction. To assess the success of the various decoding methods, a dot product metric was used. This was obtained by finding and comparing two vectors. Fig. 3 shows a schematic of these two vectors. The first vector is a desired movement vector which is a unit vector that points in the direction from the current cursor position to the target position. The second vector is determined by the decoding of the recorded signals. Each decoding scheme produced x and y values from the signals of the electrodes assigned to their respective directions. These prediction vectors were then normalized so that the mean magnitude was equal to one. The dot product of each desired unit vector and normalized prediction vector was then calculated. Finally, the mean of these dot products across all points in time was calculated. Therefore, if all of the decoding vectors pointed perfectly in the direction of the desired vectors, the mean dot product would be equal to one.

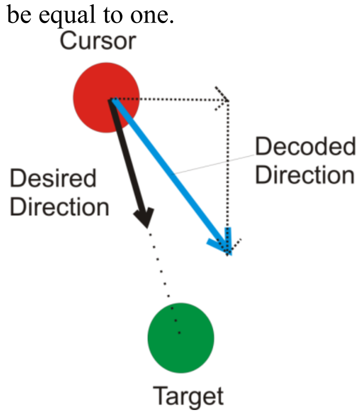

Figure 3 - Schematic showing the relationship between the cursor and target for determining the desired direction as well as a hypothetical decoded direction from x and y control signals.

This analysis was used to look at what frequency range may be best for control. Band pass filtering of the data was done with various pass bands. Then using a total lag of 700 ms, the power of the signal between 65-100 Hz was calculated. Once again the power values were decoded to give a predicted vector that was then compared with the desired vector. The average dot product metric was once again used to determine how well the predicted matched the desired. Fig. 4 shows the results for 19 different frequency pass bands. There are two main trends that emerge. First, in general, larger pass bands up to 35 Hz tend to give better results. Additionally, any band that is close to 60 Hz tends to have a poorer result presumably because of 60 Hz electrical noise. Interestingly, the 65-100 Hz band (in blue) that was actually used for control was not the best in this analysis.

Overall, it would appear that moving the center frequency higher to 90 Hz would yield better results. Additionally, it appears that for control the monkey was using most of the range of frequencies within the 65-100 Hz band. However, this analysis is biased by the control parameters that were actually used. It does appear that the larger the pass band the monkey is able to successfully modulate, the more successful control the monkey will achieve. At some upper limit, when the pass band is too wide such that the monkey is only able to control a subset of the frequencies within a band; the inclusion of a wider band in the decoding algorithm only adds noise to the system. The key will be to find the proper balance between making sure the band is not too narrow such that it slows the response but also not too wide such that unnecessary noise is added relative to the underlying signal. Based on the current data and the desire to center the control at 90 Hz to avoid 60 Hz and its first harmonic of 120 Hz, our best prediction is that 75-105 Hz (in yellow) will likely be a good choice for future control.

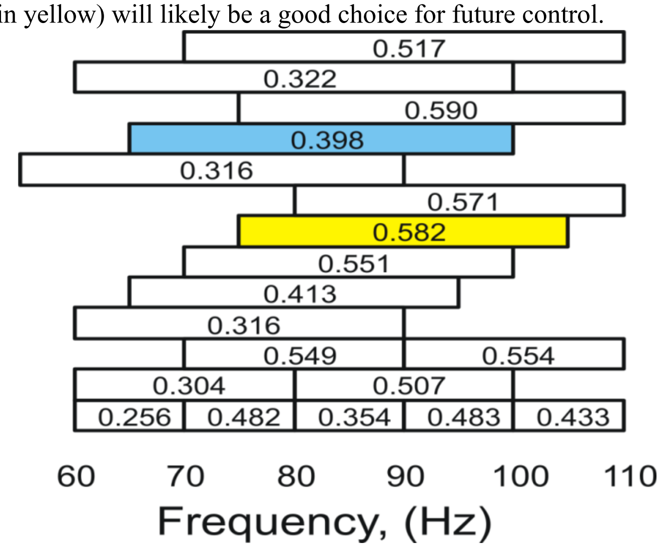

Figure 4 - The dot products using a lag of 700 ms for various pass bands. The blue represents the 65-100 Hz band used for actual control in the experiment. The yellow represents the proposed 75-105 Hz band for future control.

III. DISCUSSION

The presented studies show the important role that biofeedback and neural plasticity play in brain-computer interfaces. The ability to arbitrarily assign chosen signal features from a certain electrode to BCI cursor control allows for a reduction in the amount of open-loop screening necessary for BCI control. Additionally, electrodes that may have otherwise showed no discernable change to the subset of screening tasks used may still be potential control sites.

Also, feedback and neural plasticity allowed for more independent control using two sites in separate dimensions that were originally too close to each other to be completely uncorrelated. This opportunity to train the existing cortical architecture to realign and resize “cortical columns” to fit the dimensions of our recording electrodes offers potential for improved spatial resolution with ECoG recordings for BCI applications. This improved spatial resolution should potentially allow for ECoG based BCIs that both increase the number of degrees of freedom that can be controlled and also minimize the surgical footprint of implanted electrodes.

Overall, by being able to demonstrate successful closed loop control with epidural ECoG, steps toward a potential brain-computer interface with epidural ECoG have been taken. Additionally, this report shows that broadband amplitude modulation with a continuous filtering method provide the opportunity to achieve fast control. Also, the biofeedback provided with closed-loop BCI tasks creates the opportunity for neural plasticity to improve performance. Further testing of these predictions and chronic tests are needed to further explore the potential of epidural ECoG as a brain-computer interface modality.

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REFERENCES

[1] A. Kubler, F. Nijboer, J. Mellinger, T. M. Vaughan, H. Pawelzik, G. Schalk, D. J. McFarland, N. Birbaumer, and J. R. Wolpaw, "Patients with ALS can use sensorimotor rhythms to operate a brain-computer interface," *Neurology,* vol. 64, pp. 1775-7, May 24 2005.

[2] J. R. Wolpaw and D. J. McFarland, "Control of a two-dimensional movement signal by a noninvasive brain-computer interface in humans," *Proc Natl Acad Sci U S A,* vol. 101, pp. 17849-54, Dec 21 2004.

[3] D. M. Taylor, S. I. Tillery, and A. B. Schwartz, "Direct cortical control of 3D neuroprosthetic devices," *Science,* vol. 296, pp. 1829-32, Jun 7 2002.

[4] M. D. Serruya, N. G. Hatsopoulos, L. Paninski, M. R. Fellows, and J. P. Donoghue, "Instant neural control of a movement signal," *Nature,* vol. 416, pp. 141-2, Mar 14 2002.

[5] S. P. Levine, J. E. Huggins, S. L. BeMent, R. K. Kushwaha, L. A. Schuh, E. A. Passaro, M. M. Rohde, and D. A. Ross, "Identification of electrocorticogram patterns as the basis for a direct brain interface," *J Clin Neurophysiol,* vol. 16, pp. 439-47, Sep 1999.

[6] N. E. Crone, D. L. Miglioretti, B. Gordon, J. M. Sieracki, M. T. Wilson, S. Uematsu, and R. P. Lesser, "Functional mapping of human sensorimotor cortex with electrocorticographic spectral analysis. I. Alpha and beta event-related desynchronization," *Brain,* vol. 121 (Pt 12), pp. 2271-2299, 1998.

[7] E. C. Leuthardt, G. Schalk, J. R. Wolpaw, J. G. Ojemann, and D. W. Moran, "A brain-computer interface using electrocorticographic signals in humans," *J Neural Eng,* vol. 1, pp. 63-71, Jun 2004.

[8] J. R. Wolpaw, D. J. McFarland, G. W. Neat, and C. A. Forneris, "An EEG-based brain-computer interface for cursor control," *Electroencephalogr Clin Neurophysiol.,* vol. 78, pp. 252-259, 1991.

[9] T. Flash and N. Hogan, "The coordination of arm movements: an experimentally confirmed mathematical model," *J Neurosci,* vol. 5, pp. 1688-703, Jul 1985.

[10] R. Shadmehr and F. A. Mussa-Ivaldi, "Adaptive representation of dynamics during learning of a motor task," *J Neurosci,* vol. 14, pp. 3208-24, May 1994.