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Analysis of Amplitude Modulated Control Features for ECoG Neuroprosthetics

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***Abstract*—Electrocorticogram recordings for neuroprosthetics provide an intermediate level of abstraction between EEG and microwire single neuron recordings. For adaptive filtering methodologies used in neuroprosthetics, extraction of spatio-control parameters remains a difficulty. Since amplitude modulation in extracellular recordings plays a key role in both neuronal activation and rate coding, seeking spatial pattern classification and temporally intermittent population synchronization in terms of increased voltage may provide viable control signals. This study seeks to explore preprocessing modalities that emphasize amplitude modulation in the ECoG above the level of noise and background fluctuations in order to derive the commands for complex control tasks. The decoding performance of the amplitude modulation across the recording spectra was found to be spatially specific in the cortex.**

I. Introduction

Neuroprosthetics for communication and control have been studied at 3 levels of abstraction of signal sensing in the nervous system: scalp electroencephalogram (EEG - highest level of abstraction) [1], electrocorticogram (ECoG - intermediate level) [2], and microwire arrays (lowest level of abstraction) [3]. Analysis techniques used with each method of recording have had to contend with acknowledged facts at the microscopic level (interpreting intent from the firings of single neurons) and uncertain hypotheses at the mesoscopic levels (interpreting intent from global brain oscillations). Moreover, once the technical challenges of recording have been overcome, the task of decoding the neural intent of the individual has posed a significant challenge for signal processing methodologies [4]. The choice of available brain signals and recording methods can greatly influence the ability to extract control features, ease of clinical implementation, and operating performance. Namely, one has to decide which activity to sample, what information to extract, and how to preprocess the information. The level of neuroprosthetic performance may be attributed to selection of electrode technology, choice of model for extracting motor intent, and methods for using neuron rate, frequency, or timing codes.

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We are particularly interested in the capabilities of ECoG recordings for neuroprosthetics because they provide an intermediate level of abstraction between EEG and microwire single neuron recordings. This technology may have the ability to preserve aspects of the fine spatial microstructure of neuronal firing while accessing more global network activation on the cortex. Recent studies have shown that the modulation of single neurons and/or field potentials can explain as much as 80 percent of the variance observed in motor control tasks [5]. Therefore, harnessing both the inputs (dendritic activity) and outputs (action potentials) of neural assemblies seem to be critical for interpreting the intent of the individual. Practically, the use of the least invasive technology that provides the most complete level of neuronal resolution will provide the best compromise of patient safety and performance.

Recently, several research groups have begun using ECoG recordings from human patients in epilepsy studies and have successfully demonstrated a motor neuroprosthetic for directional cursor control tasks using frequency analysis [2]. In addition to the "proof of concept" and practical aspects of neuroprosthetic development, theoretical analysis outlined by Freeman and others has also identified the utility of ECoG potentials and attempts to explain how to extract the relevant modulation of neural assemblies. Closely spaced subdural electrodes have been reported to measure the spatially averaged bioelectrical activity of an area much smaller than several square centimeters [6]. The ability to detect and localize the mesoscopic neuronal activation (cumulative sum of EPSPs/IPSPs and action potentials across the ensemble) from ECoG electrodes is dependent upon an empirical inverse power relation (log power decreases by "$1/f^b$" , $b \sim 2 \pm 1$) [7, 8]. The biophysical attenuation properties of the neural media make the detection of fast, amplitude modulation (< 1ms) in ionic concentration difficult to detect.

For adaptive filtering methodologies used in neuroprosthetics [9], it remains unknown what are the most relevant control parameters that can be extracted from ECoG potentials. However, since we know that amplitude modulation plays a key role in both neuronal activation and rate coding, seeking spatial pattern classification and temporally intermittent population synchronization/ depolarization may be a good choice. This study seeks to explore preprocessing modalities that emphasize amplitude modulation in the ECoG above the level of noise and background fluctuations in order to derive the commands for complex motor control tasks (reaching and grasping).

Therefore, we propose to use simultaneous feature detection and model optimization to guide the selection of

features that modulate in response to motor tasks. High resolution signal analysis (12kHz sampling) with human ECoG electrode arrays will provide the experimental paradigm to derive amplitude modulations for learning the relationship between the generation of ECoG potentials collected from the surface of the motor, premotor, and parietal cortices and hand/arm movement.

II. Materials and Methods

A. Patient

The subject participating in the study was undergoing extraoperative subdural grid evaluation for the treatment of intractable complex partial epilepsy. The Patient was a 15 year old right handed, female. All experimental protocols were approved by the University of Florida IRB. Prior to ECoG subdural electrode implantation, the patient underwent a presurgical work-up that included scalp EEG, formal neuropsychological testing, and MRI. The subject's IQ and motor function was verified to be nonfocal by the absence motor or sensory deficits on neurological examination.

As a part of the standard of care, the patient was implanted with subdural grid electrodes. The surgical implantation of the electrode grids was performed according to established protocols [10] and the grids consisted of a 1.5mm thick silastic sheet embedded with platinum-iridium electrodes (4mm diameter with 2.3mm diameter exposed surface) spaced at 1-cm center-to-center distances. The approximate electrode position as indicated by the surgeon at the time of surgery is presented in Fig. 1. The anatomical location of the grids was based upon the medical team's recommendation and needs for epilepsy evaluation.

The patient involved in this study was fully recovered from the grid electrode implantation surgery within 48 hours post-surgery and was fully alert and attentive during the time of testing. During their epilepsy workup, the patient was tapered from her presurgical anticonvulsant medications (topirimate, oxcarbazepine) to facilitate seizure evaluation. When the behavioral tasks were performed, the patient was seizure free for at least 6 hours prior to testing. The primary motor cortex was determined by evoked potentials and direct electrical stimulation of the subdural grid. For the purposes of this study, the seizure focus for each patient was determined to be far from the motor region of interest.

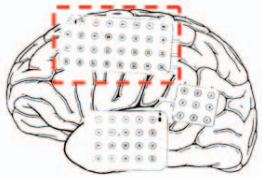

Figure 1. Electrode grid placement.

B. Behavioral Paradigm

The extraction of communication and control features from ECoG within a Brain Machine Interface (BMI) paradigm is facilitated by the ability to continuously time synchronize neuronal modulation with known variables in the external environment. This paradigm contrasts traditional epilepsy evaluations where *internal* neuronal representations are correlated with *internal* epileptic states. Here, the experimenter can gain an advantage by directly correlating internal representations with well defined behavioral tasks. A motor task for reaching and grasping was selected in this study and is defined by a movement trajectory consisting of cursor control and target selection as described below.

Concurrent with the recording of neuronal modulations from the implanted ECoG grids, the patient was cued to follow with her index finger a predefined cursor trajectory presented on an LCD screen with an active area of (20 x 30cm). The trajectory in Fig. 2 consisted of two components: a commonly used center out cursor control task [11] and a target selection [12] task. This behavior mimics a computer user's movement to select an icon on the screen. In a single session, the patient was required to repeat the entire task six times. The same trajectory was repeated for each trial.

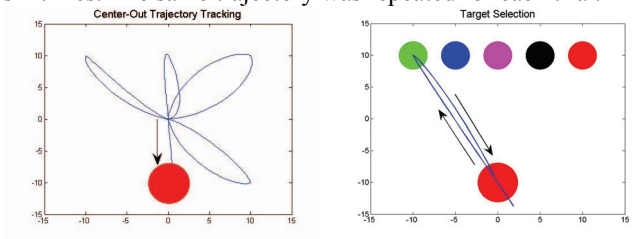

Figure 2. Behavioral trajectories 20x30cm (x – horiz., y – vert.)

C. Electrophysiological Data Collection

Multichannel subdural potentials were collected synchronously at Shands Hospital University of Florida while the patient was engaged in the behavioral task. Neuronal activity from the thirty-two electrodes indicated by the dashed box in Fig. 1 was recorded using a Tucker-Davis (Alachua, Florida) Pentusa neural recording system sampling at 12,207Hz. Based upon the patient's cytoarchitecture the electrode grid was covering the premotor, primary motor, and somatosensory cortices. The potentials from these areas were digitized with 16 bits of resolution and bandpass filtered from 1 to 6kHz. Behavioral trajectory recordings were also stored with a shared time clock and sampled at 381.5 Hz on the Pentusa system using ActiveX controls from the display system shown in Fig. 2.

D. Energy Preprocessing and Filtering

Sensorimotor ECoG rhythms have been studied extensively for assessing cortical activation for both theoretical and empirical reasons. The dynamic representations of information in distributed cortical neuronal networks have been shown to correlate with a variety of visual, auditory, and motor tasks and comprise the slow potentials (1-60Hz) [6], gamma band (60-100Hz) [13], fast gamma band (100-300Hz) [14] and ensemble depolarization (300-6kHz) [15]. One of the challenges of processing sensorimotor rhythms is that they are commonly averaged over many trials (event related potentials ERPs) to

enable extraction of the relevant information over the noise. In applications where continuous communication and control is required, averaging over many trials may not be feasible.

Here, we build upon the strengths of rate coding preprocessing that has been used extensively in single-unit BMI experiments [16]. The critical advantage of rate coding approaches is that timing information in neuronal firing is translated into amplitude information as represented in bin rates (# of spikes per unit time). Typical firing rates are computed in bins of 100ms [17]. The goal here is to employ a similar method of preprocessing in ECoG recording where sensorimotor amplitude modulations within specific bands are converted into "rate-like" codes.

We hypothesize that the amplitude modulations in each band are the result of dipole axonal and dendritic neuronal modulation. Therefore, we define the band specific amplitude modulation as the sum of the power of the ECoG [18] voltage signal in a 100ms time bin as in (1). In this paradigm we equally weight positive and negative polarizations and focus only on the amplitude. Equation (1) was computed in 100ms non-overlapping windows for each electrode over the entire dataset.

$$x(t) = \sum_{i=1}^{100ms} v(i)^2 \tag{1}$$

To compare the communication and control capabilities of the amplitude modulation with well established definitions of sensorimotor rhythms, the formulation in (1) was computed on ECoG potentials that were preprocessed by filtering between (1-60Hz, 60-100Hz, 100-300Hz, and 300-6kHz) using FIR filters adjusted for the group delay (forward-reverse filtering – filtfilt command in Matlab).

E. Modeling

To construct the mapping between neuronal modulation and behavior, a linear adaptive filter (WF) topology in Fig. 3 was trained using the Wiener solution [19]. The topology contains 32 inputs (ECoG channels), 25 tap-delays, and 2 outputs and was trained with 4 minutes (2400 samples) of neuronal and behavioral recordings. The WF utilizes the most recent 2.5 seconds of neural activity to compute each output which was optimized by scanning tap delays from 5-30 to construct the best performance. The vector form of this operation is given by (2) [17]. The optimal MSE solution is given by (3), where **d** is the hand trajectory.

$$\mathbf{y}(t) = \mathbf{W}\mathbf{x}(t) \tag{2}$$

$$\mathbf{W} = \mathbf{R}^{-1}\mathbf{P} = E(\mathbf{x}^T\mathbf{x})^{-1}E(\mathbf{x}^T\mathbf{d}) \tag{3}$$

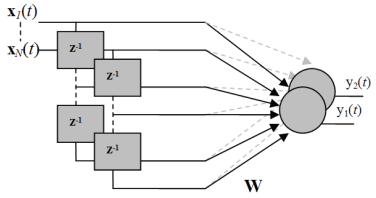

Figure 3. Wiener filter topology.

III. Performance Results

To test the ability of the model to reconstruct the trajectory from the amplitude modulated communication and control signals extracted from the ECoG, the model weights were fixed and novel neuronal recordings (2min - 1200 samples) were presented. The amount of variance in the desired trajectory that was explained by the output of the model was computed using the correlation coefficient (corrcoef – matlab command) and is presented in Table 1. Here, the output of the model was most correlated with the y-coordinate for all frequency bands. Performance tended to increase with frequency in this coordinate direction. In contrast, the x-coordinate was not predicted as well for all bands; however lower frequencies produced higher correlations for this coordinate. Representative traces are presented in Fig 4 where continuous tracking of the desired is shown using only amplitude modulated ECoG. Improvements in the tracking are shown with increasing frequency especially in the y-coordinate.

Table 1. Testing Performance

Testing Correlation Coefficient							
300 - 6kHz		100 - 3kHz		60 - 100Hz		1- 60Hz	
x	y	x	y	x	y	x	y
0.59 ± 0.30	0.74 ± 0.09	0.56 ± 0.31	0.73 ± 0.09	0.64 ± 0.25	0.71 ± 0.09	0.62 ± 0.30	0.67 ± 0.16

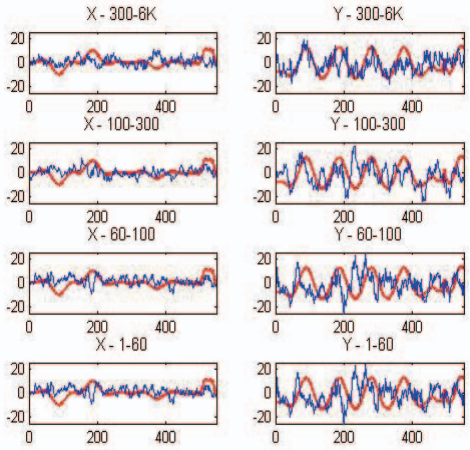

Figure 4. Representative movement trajectories (desired – bold)

IV. Physiologic Interpretation

Theoretical analysis of the spatio-temporal activation of coordinated neural ensembles has attempted to define the regions of interest involved in cortical processing. Here we derive the activation directly from the model and experimental data as a function of the analyzed frequency band. When the fitting error is small, a sensitivity analysis [17] can be performed by computing the Jacobian of the output vector with respect to each neuronal input i as shown in (4). This calculation indicates which inputs are most important for modulating the output/trajectory of the model. Hence, an electrode's importance can be determined by simply reading the corresponding weight value in the trained

model, if the input data for every channel is power normalized. Since for ECoG data this is not the case, the electrode importance is estimated in the vector Wiener filter by multiplying the absolute value of a electrode's sensitivity with the standard deviation of its amplitude computed over the dataset as in (5). To obtain a scalar sensitivity value for each electrode, the weight values are also averaged over the ten-delays and output dimensions.

$$\frac{\partial \mathbf{y}_j}{\partial \mathbf{x}_i} = \mathbf{W}_{10(i-1)+1:10(i-1)+10,j} \tag{4}$$

$$s_i = \sigma_i \frac{1}{2}\sum_{j=1}^{2}\frac{1}{25}\sum_{k=1}^{25}\left|\mathbf{W}_{10(i-1)+k,j}\right| \tag{5}$$

In Fig. 5, the normalized sensitivity contours are presented and spatially arranged to match the electrode grid in Fig. 1. Here, we see that for the 300-6kHz band the electrodes that best reconstructed the hand trajectory were highly localized in the primary motor and somatosensory cortices with less activation in the premotor cortex. The slow potentials produced diffuse activation in all three cortices. Both the gamma and high-gamma oscillations produced similar activation in the premotor cortex.

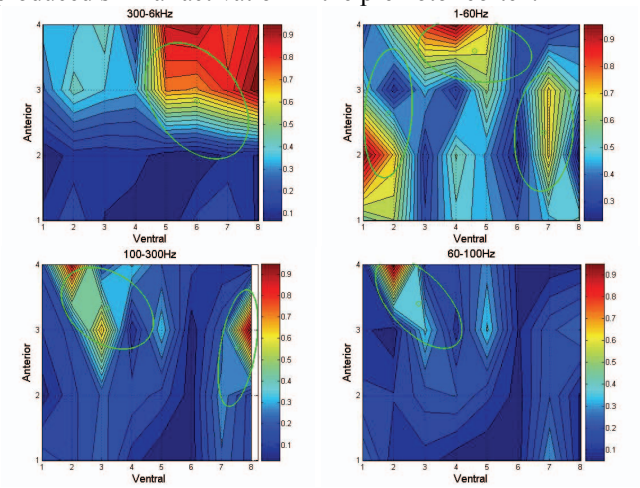

Figure 5. Regions of maximal sensitivity for each band.

V. Discussion

Defining continuously varying feature vectors from ECoG for deriving communication and control commands is a significant challenge in neuroprosthetic design. Building upon rate coding theory and observations form visual, auditory, and motor ERD studies, this analysis indicated that the computation of "rate-like" amplitude modulations provides a viable control parameter for producing neural interfaces capable of therapeutic performance. One particular advantage of such an approach is that the feature can be derived using few trials when compared to ERP style analysis. In terms or sensorimotor rhythms, all frequency bands within slow, gamma, fast-gamma, and ensemble activation produce some contribution to the task indicating a mutually inclusive approach to neuroprosthetics. Since each frequency band produces spatially distinct activation, one approach to neuroprosthetic design may be to tailor the extraction of the potentials to the patient using the signal processing techniques described here. The linking of theoretical analysis of mesoscopic neuronal activation with data driven signal processing techniques has provided a rich interpretation of the underlying physiology and provided insight for the next steps in neuroprosthetic development.

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