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Classification of hand posture from electrocorticographic signals recorded during varying force conditions

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Abstract— **In the presented work, standard and high-density electrocorticographic (ECoG) electrodes were used to record cortical field potentials in three human subjects during a hand posture task requiring the application of specific levels of force during grasping. We show two-class classification accuracies of up to 80% are obtained when classifying between two-finger pinch and whole-hand grasp hand postures despite differences in applied force levels across trials. Furthermore, we show that a four-class classification accuracy of 50% is achieved when predicting both hand posture and force level during a two-force, two-hand-posture grasping task, with hand posture most reliably predicted during high-force trials. These results suggest that the application of force plays a significant role in ECoG signal modulation observed during motor tasks, emphasizing the potential for electrocorticography to serve as a source of control signals for dexterous neuroprosthetic devices.**

I. INTRODUCTION

Restoration of functional hand grasp is frequently listed as providing the greatest potential quality-of-life improvement for individuals with tetraplegia [1]. Though functional electrical stimulation (FES) based systems have been found to be successful in providing the restoration of hand function [2], control strategies for such devices are often limited to simple switches or electromyographic control. Anthropometric prostheses [3] [4] have the capability to produce dexterous movements but require more sophisticated control signals and strategies. Brain-machine interface (BMI) technology, which aims to establish a direct link between the brain and external devices, is of particular interest here, as it may enable faster and more intuitive control of prosthetic devices for individuals with severe motor impairments.

Though neural recording modalities including single/multi-unit activity (SU/MUA) and electroencephalography (EEG) have been investigated within a BMI context, electrocorticography (ECoG) has gained particular prominence as of late owing in part to its high signal-to-noise ratio and high spatial and temporal resolution. ECoG activity has been been found to provide information about individual finger movements [5] [6] as well as whole-hand grasp [7] [8]. Though these studies have established the feasibility of the extraction of hand movement information from ECoG recordings, clinically-viable BMI prosthetic devices ultimately must be robust to forceful interactions of the prosthetic device with the external world, namely the influence of applied force on the ability to decode movement intention. While the effect of applied force on SU/MUA recordings has previously been investigated [9], to date little work has investigated the effect of the application of force on the modulation of ECoG signals.

In the presented work, three individuals with ECoG grids implanted subdurally for intractable epilepsy monitoring performed a task that required them to either pinch or whole-hand grasp a custom-made squeeze bulb with a specific amount of force. We show that hand posture can reliably be predicted from ECoG recordings across varying force conditions, with hand posture most easily predicted for high-force trials.

II. METHODS

A. Human Subjects and Behavioral Paradigm

Electrocorticographic signals were recorded from 3 subjects (2 female and 1 male, ages 12, 45, and 9) undergoing invasive monitoring for intractable epilepsy, with seizure foci and electrode placement varying across subjects. Informed consent was obtained from each subject prior to testing, with all experimental procedures approved by the University of Pittsburgh Institutional Review Board and following all guidelines for human subject research.

The experimental paradigm used for all experimental sessions is shown in Figure 1. Subjects were instructed to either pinch or grasp a rubber squeeze bulb with a specific amount of force. Subjects were instructed to perform a two-finger pinch in order to ensure that equivalent force conditions were capable of being applied in both hand postures. Visual feedback was provided in the form of a vertical bar on a computer screen displaying the current level of force being exerted on the squeeze bulb, the target force level, and the desired hand posture. Subjects were then required to apply the correct amount of force such that the feedback bar remained within a small window surrounding the target force level for a short amount of time ($\sim$100 ms). Target hand postures were randomized across trials, and target force levels were either randomized over a continuous force scale (random-force task) or between a low and high force condition (two-force task). Subjects A and B completed the

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random-force task, while Subject C performed the two-force task. Between 86 and 106 trials of hand movement data were collected per subject across multiple experimental sessions.

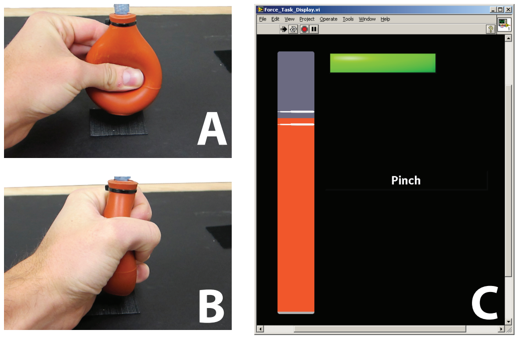

Fig. 1. Force task paradigm. *A.* Example of a two-finger pinch hand posture. *B.* Example of a whole-hand grasp hand posture. *C.* Visual stimulus. Desired hand postures were displayed to subjects on a computer screen in text format, while real-time force feedback was displayed as a vertical orange bar. Target force levels were displayed as a series of vertical white bars; subjects were then required to either pinch or whole-hand grasp a squeeze bulb with the desired level of force.

B. ECoG Recording and Preprocessing

Standard clinical ECoG grids (Ad-Tech Corp., 3mm diameter contact area, 10mm center-to-center distance) were implanted subdurally in all subjects for purposes of epilepsy monitoring. In addition, Subject B was implanted with a high-density ECoG grid (Ad-Tech Corp.) consisting of 16 disc electrodes (1.5mm diameter contact area, 4mm center-to-center distance) implanted for research purposes. ECoG signals were band-pass filtered between 0.1 and 200 Hz and sampled at 1200 Hz using the g.USBamp amplification system in conjunction with the BCI2000 software package [10]. Signals were segmented by desired hand posture and aligned to force onset prior to analysis. For each subject, a subset of 14 or 15 electrodes located over cortical areas responding to hand movement were chosen for further processing (Figure 2). Time-frequency distributions for selected electrodes were calculated using the maximum entropy method (1 Hz frequency bins, window and step sizes of 200 and 20 ms, respectively) [11], log-transformed, converted to pseudo Z-scores using baseline data collected during the same experimental session [12], and then averaged across the 8-12 Hz, 18-24 Hz, 75-115 Hz, 125-159 Hz, and 159-175 Hz frequency bands [5]. Data from multiple sessions were combined into a single data set for further analysis.

C. Dimensionality Reduction and Classification

Time-varying band power for each trial was further averaged over the [-1s 1s] time interval relative to force onset to account for variability in the temporal profiles of both hand posture and force data. The resultant feature sets consisted of time-averaged band power in 5 frequency bands for each electrode, resulting in an $N \times D$ matrix of trials (N) by features (D). Standard Principal Components Analysis (PCA) was then performed on this matrix to yield a set of D principal components (PCs) ranked by their contribution to the total variance of the data; feature reduction was performed by choosing the top M PCs for use in classification.

Gaussian Naïve Bayes (GNB) classification was used to predict either hand posture (2 classes, all subjects) or hand posture and force level (4 classes, Subject C only) using leave-one-out cross validation. To study the effect of dimensionality reduction on classification accuracy, both the original time-averaged band power data (i. e., the "high-dimensional" data) and the PCA representation of the time-averaged band power (i. e., the "low-dimensional" data) were used for classification. Classification was performed for all values of M from 1 to D (the size of the high-dimensional space, 70 for Subjects A and B and 75 for Subject C). A permutation test was utilized to determine the chance-level classification accuracy, where the class labels for each dataset were randomly permuted and re-classified 1000 times. Chance levels were calculated as the mean $\pm$ one standard deviation of the classification accuracies obtained from the permutation test, while *p*-values were determined by calculating the fraction of permuted classification results exceeding the accuracies obtained for the non-permuted data.

III. Results

Tables I and II show the results obtained for all subjects during classification of hand posture from high and low-dimensional data sets, respectively. Two-class classification accuracies of 0.42, 0.60, and 0.65 were obtained for classification of hand posture from the high-dimensional data, with the results obtained from Subjects B and C found to be statistically significant ($p < 0.05$). When classifying low-dimensional data, maximum accuracies of 0.71 ($M = 11$), 0.71 ($M = 62$), and 0.80 ($M = 17$) were found for Subjects A, B, and C, respectively. In all cases, the lower-dimensional representation of the data yielded statistically significant classification accuracies. When data from the two-force hand posture task performed by Subject C were examined, clear patterns of modulation in time-varying spectral power by applied force level were observed. Figure 3 shows the

TABLE I

Two-class hand posture classification results for high-dimensional data.

Subject	Accuracy	Chance Level	*p*-Value
A	0.417	0.498 ± 0.062	0.906
B	0.604	0.499 ± 0.063	0.036
C	0.651	0.503 ± 0.071	0.010

TABLE II

Two-class hand posture classification results for low-dimensional data.

Subject	# PCs	Accuracy	Chance Level	*p*-Value
A	11	0.705	0.501 ± 0.063	$1e-3$
B	62	0.708	0.502 ± 0.060	$< 1e-3$
C	17	0.802	0.501 ± 0.071	$< 1e-3$

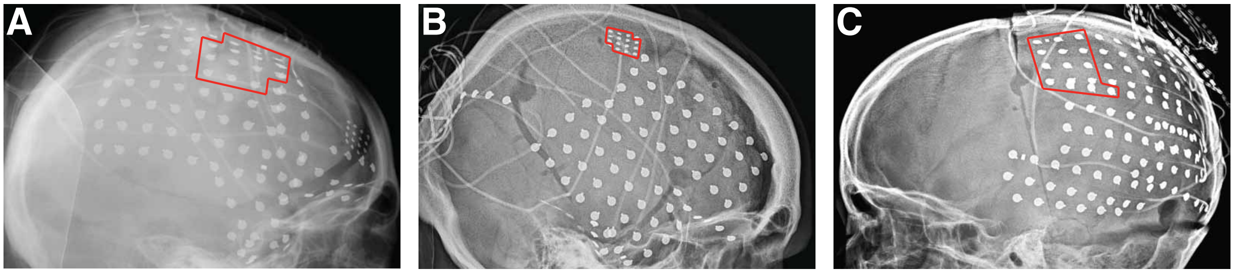

Fig. 2. Electrode locations. X-ray images showing implanted ECoG electrode grids for subjects A (left), B (center), and C (right). Though large numbers of electrodes were implanted in all subjects, analysis was restricted to 14 or 15-electrode subsets (defined by the red lines) found to be strongly modulated by the hand posture task.

normalized time-frequency data from a representative electrode averaged across trials during all four hand posture and force level conditions. Here, increased modulation of spectral power across the 60 - 140 Hz frequency band is observed for the high-force pinch condition relative to other hand posture and force level conditions.

When attempting to classify both hand posture and force level from data obtained during the two-force hand posture task, classification accuracies of 0.40 ($p < 0.007$, chance level: 0.25 ± 0.057) and 0.50 ($p < 1e-3$, chance level: 0.025 ± 0.057) were obtained using the high and low-dimensional ($M = 10$) data sets. A confusion matrix depicting these results is shown by Figure 4. It was found that high-force conditions were most easily classified, with the high-force grasp condition correctly predicted 70.8% of the time.

To further assess the effect of applied force on the ability to classify hand posture from ECoG signals, data obtained during the two-force hand posture task was separated by force condition and re-classified to predict hand posture. Here, classification accuracies of 0.54 and 0.84 were found when classifying hand posture from low and high force-level trials, respectively, using the low-dimensional ($M = 10$) representation of the data.

IV. Discussion and Conclusions

We have shown that hand posture information can be predicted from ECoG data with greater-than-chance accuracy across varying force conditions using PCA-based dimensionality reduction. Furthermore, we have also shown that force-dependent modulation of ECoG spectral power is observed during hand movement, and that higher classification accuracies are obtained when classifying ECoG data obtained during high-force trials. These results are encouraging from a BMI perspective, as they suggest that ECoG may serve as a potential source of neural signals for dexterous prosthetic devices such as the Modular Prosthetic Limb and DEKA Arm [3] [4], and that these signals may be sufficiently force-invariant to allow for prosthetic hand control across a wide range of hand posture activities which may require the application of different levels of force.

The increases in classification accuracy observed as a result of PCA dimensionality reduction are not particularly surprising, considering that Naïve Bayes classification was used to predict hand posture from the recorded data. Though spectral data was averaged over larger frequency bands prior to analysis, the substantial correlation observed across the 75-115 Hz, 125-159 Hz, and 159-175 Hz frequency bands, characteristic of broadband ECoG spectral modulation observed in other studies [13], violates the independence ("Naïve") assumption of the classifier used to predict hand posture. By using PCA for dimensionality reduction, the lower-dimensional state used for classification more appropriately fits this independence assumption, resulting in an increase in classification accuracy.

Though the hand posture classification accuracies presented here are comparable to those previously obtained from ECoG signals (79.6% two-class and 68.3% three-class classification accuracy) [14], in spite of the confounding factor of applied force, it may be possible to increase classification accuracy through improvements in task design. Here, signals were averaged over large time windows prior to classification to account for inter-trial differences in the temporal profiles of hand posture and applied force. It is possible that by enforcing greater consistency in hand posture and applied force profiles, as well as including time-varying features for classification rather than simply using time-averaged features, our ability to predict hand posture may be increased. However, it should be noted that these results provide a framework to identify the existence of a neural substrate encoding both hand posture and grasp force; our ultimate goal is to develop a functional BMI device capable of achieving continuous control over both hand posture and grasp force.

Finally, the fact that classification accuracy is greatest for high-force trials indicates that ECoG signals encoding hand posture are more discriminative for high levels of applied force than low force levels. This suggests a "gain field"-like modulation of hand posture tuning by grasp force, representing a nonlinear interaction between force and hand posture. This type of gain field activity has been observed previously for interactions between hand speed and direction [15] and between hand translation and rotation [16] using single-unit recordings. However, in order to fully assess the relationship between hand posture and grasp force a more

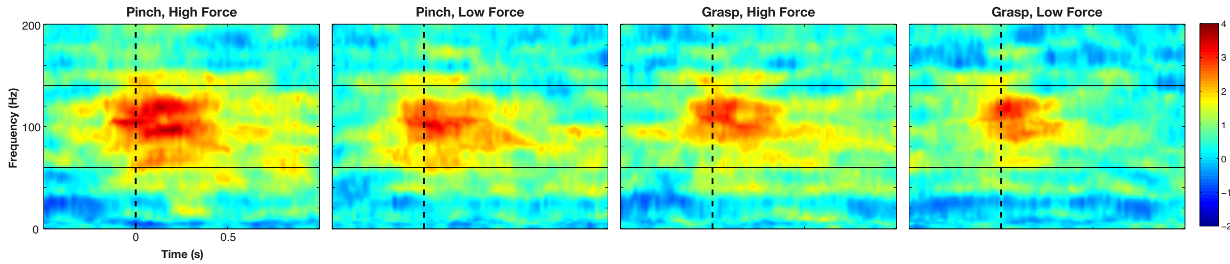

Fig. 3. Modulation of ECoG spectral power during a two-force hand posture task. Time-frequency plots of normalized spectral power averaged across between 20 and 24 repetitions per hand posture/force condition are shown for Subject C. Force onset is indicated by the dashed black line at $t = 0$, while the 60 - 140 Hz frequency band exhibiting task-related modulation is framed by the horizontal black lines at 60 Hz and 140 Hz. Qualitatively similar results were observed across multiple electrodes, with high-force conditions eliciting stronger high-frequency modulation for a particular hand posture relative to other conditions.

sophisticated paradigm utilizing the isometric application of force would likely be required to fully disassociate the effects of hand posture and applied force on ECoG signal modulation.

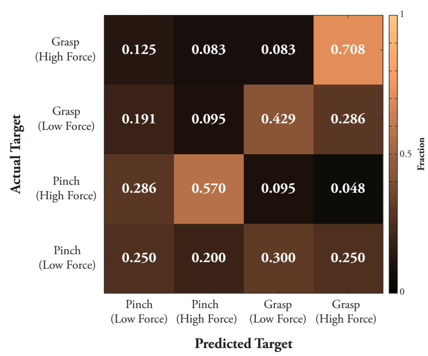

Fig. 4. Classification of hand posture and force level during a two-force hand posture task. A confusion matrix representing fractional counts of the actual (y-axis) versus predicted (x-axis) hand posture and force level during the two-force hand posture task is shown for data collected from Subject C.

In summary, the work presented here provides preliminary evidence of the effect of force and hand posture interactions on ECoG signal modulation. We have shown the ability to predict hand posture information from ECoG signals across varying levels of applied force, as well as the benefit of dimensionality reduction in the classification of highly-dimensional data sets. Finally, we have presented evidence of "gain field"-like interactions between hand posture and grasp force. These results represent an initial attempt at characterizing the effect of hand posture and grasp force on ECoG signal modulation, providing a basis for a more thorough investigation of this important relationship.

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