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Electrocorticographic Gamma Band Power Encodes the Velocity of Upper Extremity Movements

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Abstract: Subjects undergoing subdural electrode placement for epilepsy evaluation performed a series of six elementary upper extremity movements. Depending on grid location, the electrocorticographic (ECoG) signals in the high gamma band were found to encode the velocity of these movements. To the best of our knowledge, this represents the first comprehensive study of elementary upper extremity movements and their relationship to ECoG signals. This information can potentially enable brain-computer interface control of six degrees-of-freedom prostheses.

Keywords: BCI, electrocorticogram, ECoG, kinematics, high gamma band, decoding

1. Introduction

Electrocorticogram (ECoG) has been explored as an alternative signal acquisition platform to intracortical microelectrodes in brain-computer interface (BCI) control of upper extremity prostheses. Unlike their intracortical counterparts [Hochberg, 2012], ECoG electrodes do not penetrate the cortex, and may have a long-term signal stability advantage. However, how well arm, hand, and finger kinematic parameters can be decoded from ECoG remains unclear.

2. Materials and Methods

Subjects were recruited from an epilepsy patient population undergoing subdural electrode grid implantation involving the primary motor cortex. Up to 64 channels of ECoG data were recorded with two Nexus-32 amplifiers (Mind Media, The Netherlands). Signals were acquired at 2048 Hz in a common average reference mode.

Subjects were asked to perform a series of 6 elementary movements, as tolerated and as permitted by time: (1) pincer grasp/release; (2) wrist flexion (F) and extension (E); (3) forearm pronation and supination; (4) elbow flexion and extension; (5) shoulder forward flexion (FF) and extension; (6) shoulder internal rotation (IR) and external rotation (ER). Subjects first performed 4 sets of 25 continuous repetitions of each movement type (1-6), with each set intervened by a 20-30 second rest period. An electronic goniometer (movements 1-2) or gyroscope (movements 3-6) was used to measure the trajectory, (position, $\theta(t)$, and velocity, $\dot{\theta}(t)$), and their signals were acquired by an integrated microcontroller (Arduino, Smart Projects, Turin, Italy).

To determine if ECoG signals encoded the above movements, they were bandpass filtered (80-160 Hz), and their instantaneous power, $P(t)$, was calculated. $P(t)$ was visually inspected, and those movements whose $P(t)$ were deemed highly correlated with either $\theta(t)$ or $\dot{\theta}(t)$ were further analyzed by an automated decoding system. This system performed classification to determine idling and movement epochs from ECoG signals, followed by trajectory decoding during those epochs that were classified as movement.

Half of the ECoG data was used to train the decoding system while the other half was used for testing. Subsequently, the roles of these data segments were reversed and the above procedure was repeated. To classify ECoG into idling and movement states, a linear regression model was first generated between $\dot{\theta}(t)$ and $P(t)$. A pair of thresholds was then applied to the estimate $\hat{\dot{\theta}}(t)$ to determinate the transitions from idling to movement states, and vice versa. The threshold values were found by minimizing the mismatch between the estimated state transitions and the ground truth, as determined by the measured trajectory. Subsequently, from $\dot{\theta}(t)$ and $P(t)$ corresponding to movement epochs, a second linear regression model (trajectory decoder) was generated to estimate $\hat{\dot{\theta}}(t)$.

Offline estimates $\hat{\dot{\theta}}(t)$ were determined by first classifying the test ECoG data into either idling or movement classes. For each ECoG epoch classified as idling, $\hat{\dot{\theta}}(t)$ was set to 0. Conversely, for epochs classified as movement,

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$\hat{\dot{\theta}}(t)$ was estimated by the trajectory decoder. The correlation coefficient between $\dot{\theta}(t)$ and $\hat{\dot{\theta}}(t)$ for each movement type was calculated.

3. Results

Three subjects were recruited for this study. During visual inspection, $P(t)$ was found to be visually correlated with trajectory for several movements. The classification and trajectory decoding results for each of these movements are summarized in Table 1. A representative velocity decoding is shown in Fig. 1.

Table 1. *Summary of results, showing study subjects, subdural electrode placement description, movements represented by visual inspection of signal, and results of classification and trajectory decoding system. Note that results are reported in pairs, corresponding to the two validation sets (see Section 2).*

Subject	Movements Represented (Visual Inspection)	Idle/Movement Accuracy (Ratio Correctly Decoded)	Trajectory Decoding Accuracy (X-Correlation)
S1 (20 yo F, Left 8x8 temporal-frontal grid, 1x6 posterior frontal strip)	Grasp, Wrist	Grasp: 0.85, 0.81 Wrist: 0.89, 0.83	Grasp: 0.68, 0.66 Wrist: 0.46, 0.52
S2 (27 yo F, Right frontal-parietal 6x8 grid)	Grasp, Elbow, Shoulder	Grasp: 0.73, 0.89 Elbow: 0.80, 0.80 Shoulder IR/ER: 0.68, 0.80 Shoulder FF/E: 0.82, 0.87	Grasp: 0.54, 0.62 Elbow: 0.44, 0.53 Shoulder IR/ER: 0.62, 0.53 Shoulder FF/E: 0.53, 0.69
S3 (35 yo F, Right frontal-parietal 2x6 strip)	Grasp	Grasp: 0.89, 0.88	Grasp: 0.62, 0.64

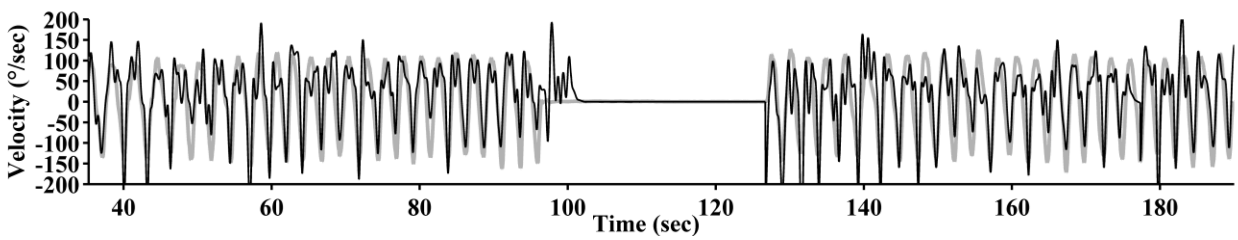

Figure 1. *ECoG-decoded (thin line) and measured (thick line) velocities during shoulder FF/E for Subject S2.*

4. Discussion

The results here indicate that velocities of elementary upper extremity movements are encoded within the power of ECoG signals in the high gamma band. The ability to decode these movements can eventually translate to the full BCI control of a 6-degrees-of-freedom upper extremity prosthesis. Such level of control may be necessary to adapt to the many unique situations presented in everyday life and may be a requisite to restoring independence to those with upper extremity paralysis. There have not been previous comprehensive efforts to elucidate the decoding of these movements from ECoG signals, and the results presented here bolster the potential of using ECoG signals for BCI-controlled upper extremity prostheses.

A combination of classification and regression was used to decode movement trajectories from ECoG signals. The most salient features encoding for movement kinematics were found in the high gamma band (80-160 Hz). These findings are consistent with prior studies [Miller, 2007]. The gamma band likely represents cortical activity of the neuronal generators controlling each of these movement types. Given the anatomical proximity of these generators in the motor cortex, future work will focus on investigating the discriminability of these movements.

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References

Hochberg LR, Bacher D, Jarosiewicz B, Masse NY, Simeral JD, Vogel J, Haddadin S, Liu J, Cash SS, van der Smagt P, Donoghue JP. Reach and grasp by people with tetraplegia using a neurally controlled robotic arm. *Nature*, 485(7398):372-375, 2012.

Miller KJ, Leuthardt EC, Schalk G, Rao RP, Anderson NR, Moran DW, Miller JW, Ojemann JG. Spectral changes in cortical surface potentials during motor movement. *J Neurosci*, 27:2424–2432, 2007.