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Decoding grasp force profile from electrocorticography signals in non-human primate sensorimotor cortex

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ABSTRACT

The relatively low invasiveness of electrocorticography (ECoG) has made it a promising candidate for the development of practical, high-performance neural prosthetics. Recent ECoG-based studies have shown success in decoding hand and finger movements and muscle activity in reaching and grasping tasks. However, decoding of force profiles is still lacking. Here, we demonstrate that lateral grasp force profile can be decoded using a sparse linear regression from 15 and 16 channel ECoG signals recorded from sensorimotor cortex in two non-human primates. The best average correlation coefficients of prediction after 10-fold cross validation were 0.82 ± 0.09 and 0.79 ± 0.15 for our monkeys A and B, respectively. These results show that grasp force profile was successfully decoded from ECoG signals in reaching and grasping tasks and may potentially contribute to the development of more natural control methods for grasping in neural prosthetics.

1. Introduction

Brain machine interfaces (BMIs) hold promise as a means for disabled individuals to control external devices using neural activity. In the past two decades, invasive methods have been wildly used to control robot arms and other neural prosthetics in rats (Chapin et al., 1999; Koralek et al., 2012), monkeys (Wessberg et al., 2000; Taylor et al., 2002; Carmena et al., 2003; Musallam et al., 2004; Velliste et al., 2008; Ganguly et al., 2011; Ethier et al., 2012; Gilja et al., 2012; Hauschild et al., 2012; Hao et al., 2013), and humans (Hochberg et al., 2006, 2012; Collinger et al., 2013), using neural signals such as spiking activity and local field potential. Muscle activity (Morrow and Miller, 2003; Koike et al., 2006), reach and grasp kinematics (Zhuang et al., 2010; Bansal et al., 2011, 2012) and dexterous finger motions (Aggarwal et al., 2008) during real movement have also been decoded in monkeys. Despite these successes, however, the penetration of the brain with invasive methods has remained a serious bottleneck for practical clinical solutions in humans.

Electrocorticography (ECoG) signal presents a potential alternative for supporting high accuracy BMIs because of its comparatively lower invasiveness. ECoG has seen wide clinical use, with electrodes commonly being implanted to localize seizure foci for the treatment of epilepsy in humans. This has also allowed for the investigation of ECoG-based BMI in humans, including studies on cursor control (Leuthardt et al., 2004; Schalk et al., 2008; Wang et al., 2013), classification of hand movement (Chin et al., 2007; Yanagisawa et al., 2009, 2011), and grasp types (Pistohl et al., 2012), detection of grasp initiation (Pistohl et al., 2013), and decoding of hand trajectories (Schalk et al., 2007; Chao et al., 2010; Shimoda et al., 2012; Nakanishi et al., 2013; Chen et al., 2013) and finger movement (Kubanek et al., 2009; Acharya et al., 2010). Prediction of muscle activity (Shin et al., 2012) and movement-related intracortical activity (Watanabe et al., 2012) from ECoG signals during reaching and grasping movements in monkeys have also been successful. Despite the importance of grasping force in everyday life, the prediction of grasp force profile during reaching and grasping movement has remained lacking yet.

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The aim of this study was to decode grasp force profile from ECoG signals recorded from the primary sensorimotor areas. Fifteen and sixteen channel ECoG signals were recorded from the primary sensorimotor cortex in Japanese monkeys while performing reaching and grasping tasks. A sparse linear regression method was employed to decode grasp force profile. Our results demonstrate accurate decoding of grasp force profile from ECoG signals and the efficacy of high γ bands in decoding.

2. Materials and methods

2.1. Ethics statement

All experimental procedures were performed in accordance with the Guidelines for Proper Conduct of Animal Experiments by the Science Council of Japan and approved by the Committee for Animal Experiments at the National Institutes of Natural Sciences (Approval No.: 11A157). Steps were taken to ensure the animals' welfare and ameliorate suffering in accordance with the recommendations of the Weatherall report, "The use of non-human primates in research."

2.2. Monkey subjects and experimental procedure

Here, we describe our main experimental procedures. Details on these procedures can be found in our previous works (Watanabe et al., 2012; Shin et al., 2012; Chen et al., 2013). We trained two Japanese monkeys (monkey A: male, 8.9 kg; monkey B: female, 4.7 kg) to reach for and grasp a small plastic knob at the end of joystick with the right hand, repeatedly and continuously. Totals of 134 and 248 trials were performed by monkeys A and B, respectively.

2.3. ECoG and force data collection

A thin-film force sensor (FlexiForce; Tekscan, Inc., South Boston, MA) was attached to the surface of a knob to measure grasp force. As shown in Fig. 1, 15 (monkey A: 5 × 3 grid) and 16 (monkey B: 4 × 4 grid, with one electrode in the somatosensory cortex) channel ECoG electrode arrays (Unique Medical Corporation, Tokyo, Japan) were implanted in the left primary sensorimotor areas, for monkeys A and B, respectively. Locations of these electrode arrays were identified from anatomical views during surgeries and postoperative X-ray image (monkey B) or observation with craniotomy after perfusion (monkey A). The electrodes had a diameter of 1 mm and an inter-electrode distance of 3 mm center-to-center. ECoG signals and lateral grasp force were recorded simultaneously during the grasping task at 4 kHz with an acquisition processor system (Plexon MAP System; Plexon, Inc., Dallas, TX) and down-sampled to 500 Hz for data processing.

2.4. Decoding algorithm and data analysis

We detected the start and end time points for grasping from the position of the wrist marker, a on and off target sensor information on joystick (Shin et al., 2012; Chen et al., 2013). The start point (time point 0 in Fig. 2) was defined as the time point when the monkeys touched the knob, and the end point was defined as the time point when the monkeys released the knob. Both points were confirmed using target sensor data. Average grasping durations with standard deviations (STD) for monkeys A and B were 1.86 ± 0.21 s and 0.52 ± 0.17 s, respectively (Fig. 2). Thus, the duration of each trial was set to 2 s and 0.7 s in force profile prediction monkeys A and B, respectively. Tenfold cross validation was employed to counteract over-fitting, with each fold containing 11 and 24 test trials for monkeys A and B, respectively.

In preprocessing, raw ECoG signals were common average referenced and band-pass filtered, using ten different sensorimotor frequency band-pass filters: δ (1.5–4 Hz), θ (4–8 Hz), α (8–14 Hz), β1 (14–20 Hz), β2 (20–30 Hz), γ1 (30–50 Hz), γ2 (50–90 Hz), γ3 (90–120 Hz), γ4 (120–150 Hz), and γ5 (150–200 Hz). Band-passed ECoG signals were then smoothed with a Gaussian filter (width: 0.1 s; σ 0.04 s). Finally, the smoothed ECoG signals at time t, $sECoG_{ij}(t)$, were z-score normalized to produce the final ECoG source signal $z_{ij}(t)$ such that

$$z_{ij}(t) = \frac{sECoG_{ij}(t) - \mu_{ij}}{\sigma_{ij}} \tag{1}$$

where i and j are the electrode channel and frequency band, respectively, and μ_{ij} and σ_{ij} are the mean and standard deviation of $sECoG_{ij}(t)$ over a 2 s interval before time t, respectively.

Force data were also low-passed filtered at a cutoff of 4 Hz (100th order window-based finite impulse response filter). Then, the low-passed force data were normalized to the maximum value of each trial to produce the force profile.

A sparse linear regression method was employed to train a decoding model using ECoG feature signals. Sparse estimation methods are expected to be useful for extracting significant information from redundant and numerous dataset. We used the sparse linear regression algorithm, which has a generalization capability for unknown datasets due to its ability to remove irrelevant features, avoid over-fitting of the datasets. The grasp force profile at time t, $F_p(t)$, was decoded using the ECoG feature signal $z_{ij}(t)$ over a 0.6 s interval before time t and can be described as

$$F_p(t) = \sum_{i=1}^{15\,\text{or}\,16} \sum_{j=1}^{10} \sum_{k=0}^{19} \omega_{ijk} z_{ij}(t - k\Delta t) + \omega_0 \tag{2}$$

where p is the predicted value of the grasp force profile, Δt is 30 ms, ω_{ijk} are the weights according to the ECoG feature signal $z_{ij}(t)$ at electrode channel i, frequency band j, and time $t - \Delta t$, and ω_0 is the bias.

Weights of the prediction model were analyzed to evaluate the contribution of each electrode and frequency band. The contribution of each electrode Con_e, each frequency band Con_{fb} and the contribution matrix of electrodes and frequency bands Con_{efb} were calculated as

$$Con_e(i) = \frac{\sum_j \sum_k \left|\omega_{ijk}\right|}{\sum_i \sum_j \sum_k \left|\omega_{ijk}\right|} \tag{3}$$

$$Con_{fb}(j) = \frac{\sum_i \sum_k \left|\omega_{ijk}\right|}{\sum_i \sum_j \sum_k \left|\omega_{ijk}\right|} \tag{4}$$

$$Con_{efb}(i,j) = \frac{\sum_k \left|\omega_{ijk}\right|}{\sum_i \sum_j \sum_k \left|\omega_{ijk}\right|} \tag{5}$$

where ω_{ijk} are the weights according to the ECoG feature signal $z_{ij}(t)$ at electrode channel i, frequency band j, and time $t - \Delta t$.

Analysis of variance (ANOVA) was performed using MATLAB (MathWorks, Natick, MA) to detect significant effects of Con_e and Con_{fb}. A two-way ANOVA with the Tukey–Kramer test was applied to detect significant effects of Con_{efb}. In addition, force profile was predicted using each of the 10 frequency bands of the ECoG feature signals to investigate their individual contributions to prediction. Correlation coefficient (CC) and normalized root mean square error (nRMSE) between actual and predicted force profiles were used to evaluate prediction performance.