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Decoding Three-Dimensional Hand Kinematics from Electroencephalographic Signals

Trent J. Bradberry, Rodolphe J. Gentili, and José L. Contreras-Vidal

Abstract—**The capacity to decode kinematics of intended movement from neural activity is necessary for the development of neuromotor prostheses such as smart artificial arms. Thus far, most of the progress in the development of neuromotor prostheses has been achieved by decoding kinematics of the hand from intracranial neural activity. The comparatively low signal-to-noise ratio and spatial resolution of neural data acquired non-invasively from the scalp via electroencephalography (EEG) have been presumed to prohibit the extraction of detailed information about hand kinematics. Here, we challenge this presumption by attempting to continuously decoding hand position, velocity, and acceleration from 55-channel EEG signals acquired during three-dimensional center-out reaching from five subjects. To preserve ecological validity, reaches were self-initiated, and targets were self-selected. After cross-validation, the overall mean correlation coefficients between measured and reconstructed position, velocity, and acceleration were 0.2, 0.3, and 0.3 respectively. These modest results support the continued development of non-invasive neuromotor prostheses for movement-impaired individuals.**

I. Introduction

Brain-controlled devices such as neuromotor prostheses possess the potential to improve or restore the ability of movement-impaired individuals to interact with their environment in real time. In an effort to bring these types of brain-computer interface (BCI) systems to fruition, hand trajectories, velocity profiles, and acceleration profiles have been decoded from intracranial neural signals and, in some cases, used to command a cursor or robotic arm in real time [1-9]. In contrast, studies that have employed electroencephalography (EEG) to acquire non-invasive signals from the scalp have not focused on decoding detailed kinematics of natural hand movements. Instead, these EEG studies have typically involved discrete classification of the direction of two-dimensional hand movement or different motor imagery tasks on a single-trial basis [10-13] or continuous two-dimensional control of a cursor through biofeedback training [14]. The lack of attention to decoding kinematics of natural hand movements from EEG signals could be partly due to the common belief that extracranially acquired signals do not possess a sufficient signal-to-noise ratio or spatial resolution to decode this type of detailed information [15].

Casting doubt on this notion, several recent studies have decoded two-dimensional hand / tool kinematics from neural activity acquired from the scalp via magnetoencephalography (MEG) [16-19]. Motivated by these findings and the impracticability of a portable MEG-based neuromotor prosthesis, we sought to continuously extract hand trajectories, velocity profiles, and acceleration profiles from EEG signals collected during a three-dimensional center-out reaching task. Furthermore, to maintain ecological integrity, we did not cue subjects. They chose which target to acquire and when to initiate movement.

T. J. Bradberry is with the Fischell Department of Bioengineering, University of Maryland, College Park, MD 20742 USA (corresponding author, e-mail: trentb@umd.edu).

R.J. Gentili is with the Department of Kinesiology and Graduate Program in Neuroscience and Cognitive Science, University of Maryland, College Park, MD 20742 USA (e-mail: rodolphe@umd.edu). He is supported by La Fondation Motrice, Paris, France.

J. L. Contreras-Vidal is with the Department of Kinesiology, Fischell Department of Bioengineering, and Graduate Program in Neuroscience and Cognitive Science, University of Maryland, College Park, MD 20742 USA (e-mail: pepeum@umd.edu).

II. Methods

A. Experimental Procedure and Data Collection

The Institutional Review Board of the University of Maryland at College Park approved the experimental procedure. After giving informed consent, five healthy, right-handed subjects sat upright in a chair and executed self-initiated center-out reaches to self-selected push button targets near eye-level. We instructed subjects to attempt to make uniformly distributed random selections of the eight targets without counting. The elbow of the reaching arm was unsupported, and the non-reaching arm relaxed in the lap. To help prevent eye movements from contaminating the data, subjects were instructed to fixate an LED on the center target throughout data collection and to only blink when their hand was resting at the center target. To ensure the absence of eye movements, a researcher monitored the subjects' eyes during data collection, and electro-ocular activity was collected for off-line verification. For each subject, the experiment concluded after each target was acquired at least ten times.

Neural signals were recorded using an Electro-Cap with 64 sensors placed on the head according to the extended International 10-20 system with ear-linked reference. Continuous EEG signals were sampled at 1000 Hz and amplified 500 times via a Synamps acquisition system and Neuroscan software. Additionally the EEG signals were band-pass filtered from 0.5 to 100 Hz and notch filtered at 60 Hz. Electro-ocular activity was measured with a bipolar sensor montage with sensors attached superior and inferior to the orbital fossa of the right eye for vertical eye

movement and to the external canthi for horizontal eye movement. Hand position was sampled at 100 Hz using an Optotrak motion sensing system that tracked an infrared LED secured to the finger tip with double-sided adhesive tape. To aid the reader in visualization of the hand paths, Figure 1 displays the paths of Subject 1 oriented within the Cartesian coordinate system employed. Event markers of push button presses and releases were sent from the apparatus containing the push buttons to the Neuroscan and Optotrak systems for off-line synchronization of EEG and kinematic data.

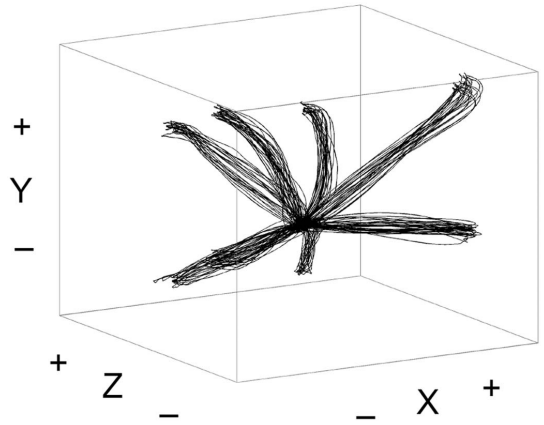

Fig. 1. Examples of hand paths of Subject 1 for center-out reaches to eight targets. The horizontal (x), vertical (y), and depth (z) dimensions of movement were respectively defined as right (+) / left (-), up (+) / down (-), and away (+) / toward (-). The distance from the center position to each of the targets was approximately 21.6 cm. Subjects took approximately 4 s to execute a single center-out reach and return to the center position.

B. Signal Pre-processing

For computational efficiency and to match the sampling rate of the kinematic data, the EEG data were decimated from 1 kHz to 100 Hz by applying a low-pass anti-aliasing filter with a cutoff frequency of 40 Hz and then downsampling by a factor of 10. Data from each EEG sensor were standardized:

$$S_n[t] = \frac{s_n[t] - \bar{s}_n}{SD_{s_n}} \quad \text{for all } n \text{ from 1 to } N \tag{1}$$

where $S_n[t]$ and $s_n[t]$ are respectively the standardized and measured voltage at sensor n at time t, $\bar{s}_n$ and SD_{s_n} are the mean and standard deviation of s_n respectively, and N is the number of sensors. We obtained the best decoding results when both the EEG and kinematic data were subsequently filtered with a zero-phase, fourth-order, low-pass Butterworth filter with a cutoff frequency of 2 Hz. Low-frequency bands have previously been found to carry kinematic information [12,18,19].

C. Decoding Model and Cross-Validation

To continuously decode hand position from the EEG signals, a linear decoding model was employed [16]:

$$x[t] = a_x + \sum_{n=1}^{N}\sum_{k=0}^{L} b_{nkx} S_n[t-k] \tag{2}$$

$$y[t] = a_y + \sum_{n=1}^{N}\sum_{k=0}^{L} b_{nky} S_n[t-k] \tag{3}$$

$$z[t] = a_z + \sum_{n=1}^{N}\sum_{k=0}^{L} b_{nkz} S_n[t-k] \tag{4}$$

where $x[t]$, $y[t]$, and $z[t]$ are the horizontal, vertical, and depth positions of the hand at time sample t respectively, N is the number of EEG sensors, L is the number of time lags, $S_n[t-k]$ is the voltage measured at EEG sensor n at time lag k, and the a and b variables are weights obtained through multiple linear regression. For velocity decoding, the same equations were used with $x[t]$, $y[t]$, and $z[t]$ replaced by their approximate first-order derivatives: $x[t]-x[t-1]$, $y[t]-y[t-1]$, and $z[t]-z[t-1]$. The approximate first-order derivatives of velocity were used for acceleration decoding. The number of lags (L=10, corresponding to 100 ms) was chosen based on a previous study that decoded kinematics from neural signals acquired with MEG [18]. The three most frontal sensors (FP1, FPZ, and FP2 of the International 10-20 system) were excluded from the analysis to further ensure that eye movements would not affect decoding, resulting in an N of 55 sensors.

For each subject, the collected continuous data contained approximately 80 trials. An 8x8-fold cross-validation procedure was employed to assess the decoding accuracy. In this procedure, data were divided into 8 parts, 7 parts were used for training, and the remaining part was used for testing. The procedure was considered complete when each of the 8 combinations of training and testing data were exhausted, and the mean correlation coefficient (CC) between measured and decoded kinematics was computed across folds. Prior to computing the CC, the kinematic signals were smoothed with a fourth-order, low-pass Butterworth filter with a cutoff frequency of 2 Hz.

III. Results

The mean and standard error of the mean (SEM) of the CCs between measured and decoded trajectories, velocity profiles, and acceleration profiles are shown in Figure 2. Variation in decoding accuracy among subjects was evident, but some general trends were apparent. The overall mean CCs for position, velocity, and acceleration were 0.2, 0.3, and 0.3 respectively. The depth dimension (z) was best decoded followed by the vertical dimension (y) then the horizontal dimension (x). For x and y, the grand mean CCs of velocity and acceleration were similar and greater than that for position. For z, the grand mean CCs for velocity and acceleration were also greater than that for position, but the grand mean CC for acceleration was noticeably greater than that for velocity. Examples of smoothed, reconstructed kinematics visually matched the measured kinematics well (Fig. 3).

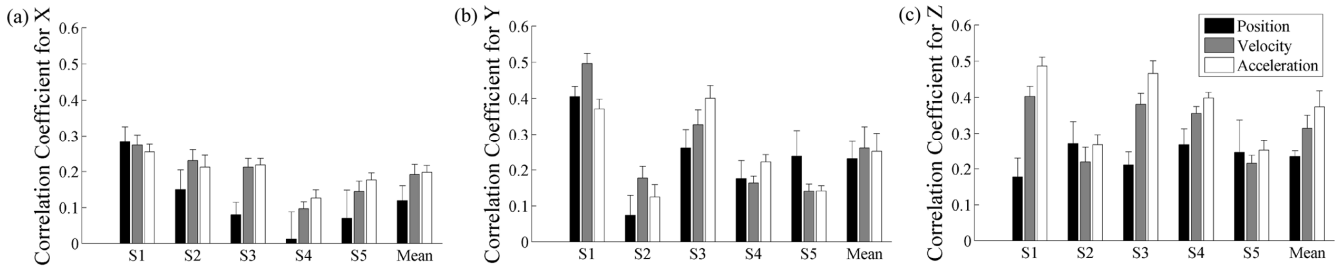

Fig. 2. Mean (n = 8) and SEM (error bar) of the CCs between measured and decoded kinematics for x (a), y (b), and z (c). Decoding results are displayed individually for each of the five subjects (S1 through S5) and collectively across subjects (grand mean). For each dimension, the results for position, velocity, and acceleration are represented with shading from dark to light respectively.

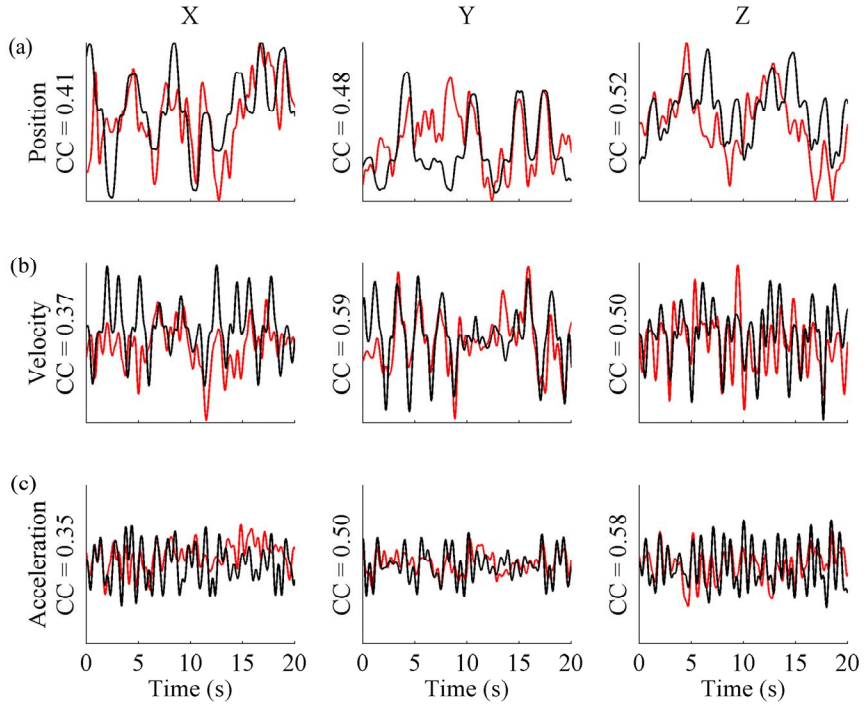

Fig. 3. Examples of standardized and smoothed measured (black) and decoded (red) trajectories (a), velocity profiles (b), and acceleration profiles (c) from Subject 1. The left column is for x, the middle column for y, and the right column for z. The CCs between measured and decoded kinematic variables are listed for each plot.

IV. Discussion

The extent to which kinematic information about hand movements may be decoded from EEG signals is currently unknown. To address this gap, we demonstrated that three-dimensional hand kinematics of natural, multi-joint, center-out movements are continuously decodable from EEG signals.

A. Process Control vs. Goal Selection

A current research question within the community of neural prostheses researchers is whether process control or goal selection is the most appropriate strategy for BCI systems [20]. Process control seeks to provide continuous interaction at high-speeds with movement of the end effector fully controlled by the subject. Goal selection requires decoding only the target to be acquired with the details of how to move the end effector handled by software. Most scalp recordings employ goal selection presumably, in part, due to the presumption that non-invasive signals do not possess detailed decodable information required for process control [15]. In contrast, studies using intracranial recordings have largely implemented process control. While we acknowledge that the best choice of strategy is far from clear, we chose to investigate a research question related to process control because, to our knowledge, process control has not been achieved using EEG signals associated with natural, multi-joint, three-dimensional center-out hand movements.

B. EEG Decoding Studies

The most common objective of EEG decoding studies is the discrete classification of single trials of overt or covert motor tasks related either directly [11,12] or indirectly [10,13] to the desired movement. An exceptional series of EEG studies achieved process control by training subjects to modulate sensorimotor rhythms to control a cursor in two-dimensions [14,21]. Besides our study incorporating an extra spatial dimension, it differs from [14,21] by decoding natural movements to better elucidate the neural code for hand movement. We believe that a clearer representation of the neural code will significantly reduce the time required to train subjects to use a BCI system. The fact that we only need about 280 s (70 trials) of training data for each subject supports our assertion.

C. MEG Decoding Studies

To our knowledge, only three studies with scalp recordings explicitly sought continuous decoding of hand / tool kinematics, all using MEG [16-19]. Neither [16] nor [17] employed center-out movements that are the standard for comparison among decoding studies associated with BCI systems. In [18,19], a cued, center-out, two-dimensional drawing task was employed, and the CCs between measured and decoded hand kinematics were higher than those of the current study. The source of this discrepancy in accuracy is uncertain but could be due to any of the following unique

characteristics of the current study: three-dimensional movement, greater extent of multi-joint movement, self-initiated movement, self-selected targets, and visual feedback provided only through peripheral vision. While MEG is a helpful tool for non-invasive decoding studies, its confinement to a laboratory setting renders it unsuitable for a wearable ambulatory system.

D. Intracranial Decoding Studies

Most intracranial studies that decoded neuronal signals acquired with microwires or microelectrode arrays aimed to implement process control of a cursor of robotic arm [1-4,8,9]. While most other intracranial studies decoded local field potential (LFP) recordings for goal selection, some exceptional LFP studies were also motivated by process control strategies [5-7]. One of the most striking results of our study is that, regardless of the fact that activity recorded at an EEG sensor constitutes the firing of millions of neurons, hand kinematics can be decoded from EEG. In addition to the advantage of the non-invasive nature of EEG, this modality captures a more global representation of the neural system being decoded.

E. Eye and Muscle Movements Did Not Aid Decoding

Undesirable electrical activity from eye or muscle movements potentially confounds the interpretation of results from EEG, MEG, and ECoG studies [22]. In our study, to ensure that eye movements did not aid decoding, we required subjects to fixate a central location for the duration of the experiment and to only blink when their hand was at the central location. We visually monitored their eyes to ensure the absence of movement as well as recorded horizontal and vertical electrooculograms for off-line analysis. Regarding muscle activity, we ran the decoding analysis after low-pass filtering the kinematics at 2 Hz. Since muscle activity is unlikely to exist below this cutoff frequency, we affirm the unlikelihood that muscle activity aided decoding.

V. Conclusion

In conclusion, we countered the prevailing notion that EEG signals do not possess decodable information about detailed, complex hand movements. In the future, we plan to investigate the feasibility of real-time control of a cursor or virtual arm by decoding imagined three-dimensional hand movements. Our expectation is that, by providing subjects with visual feedback of the decoder output, they will adapt their EEG signals to overcome any deficiencies in off-line decoding accuracy. We hope that this study serves to encourage continued advances in non-invasive BCI systems for controlling neuromotor prostheses in real time.

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