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Decoding fingertip trajectory from electrocorticographic signals in humans

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ABSTRACT

Seeking to apply brain–machine interface technology in neuroprosthetics, a number of methods for predicting trajectory of the elbow and wrist have been proposed and have shown remarkable results. Recently, the prediction of hand trajectory and classification of hand gestures or grasping types have attracted considerable attention. However, trajectory prediction for precise finger motion has remained a challenge. We proposed a method for the prediction of fingertip motions from electrocorticographic signals in human cortex. A patient performed extension/flexion tasks with three fingers. Average Pearson's correlation coefficients and normalized root-mean-square errors between decoded and actual trajectories were 0.83–0.90 and 0.24–0.48, respectively. To confirm generalizability to other users, we applied our method to the BCI Competition IV open data sets. Our method showed that the prediction accuracy of fingertip trajectory could be equivalent to that of other results in the competition.

1. Introduction

Brain–machine interface (BMI) technology has the potential to offer practical neuroprostheses for the physically impaired. For the purpose of realizing an useful neuroprostheses, trajectory prediction and classification of arm motion have been proposed in a number of studies using intracortical electrodes, electrocorticography (ECoG), electroencephalography, and other methods (Wessberg et al., 2000; Koike et al., 2006; Waldert et al., 2008; Yanagisawa et al., 2009; Chao et al., 2010; Watanabe et al., 2012; Shimoda et al., 2012; Shin et al., 2012; Nakanishi et al., 2013; Chen et al., 2013). Several studies have targeted not only the elbow and wrist but also the hand and fingers as the next step toward practical hand-arm robots that are usable in daily life. Such studies have included the prediction of grasping force (Carmena et al., 2003) or aperture (Artemiadis et al., 2007; Zhuang et al., 2010), open/close control of a gripper in primates (Velliste et al., 2008), grasping movement control of an occupational therapy assist suit for humans (Sakurada et al., 2013), onset detection of hand extension (Bashashati et al., 2007) and grasping (Pistohl et al., 2013), classification of grasping type in monkeys (Stark and Abeles, 2007) and in humans (Yanagisawa et al., 2011; Pistohl et al., 2012; Chestek et al., 2013). These predictions are very important steps to realizing a neuroprosthesis, however, the prediction of finger motion is more important for the consideration of a practical use.

In our everyday life, we perform complicated finger motion, such as controlling a smart phone and tablet, operating a remote controller of home electronics, and playing musical instruments. The prediction of three-dimensional finger motion is the most necessary function to interact with environments for quadriplegia. Several ECoG-based studies reported the prediction of individual finger flexion, i.e. one degree of freedom for each finger in humans using ECoG (Miller et al., 2009; Kubanek et al., 2009; Acharya et al., 2010; Liang and Bougrain, 2012). Since ECoGs have showed better characteristics such as higher spatio-temporal resolution, good signal-to-noise ratio, and long-term recording than scalp EEG and

Abbreviations: ECoG, electrocorticography; BCI, brain–computer interface; BMI, brain–machine interface; CC, Pearson's correlation coefficient; nRMSE, normalized root-mean-square error; LOO-CV, leave-one-out cross validation; CAR, common average reference; SEM, standard error of the mean; MP joint, metacarpal phalangeal joint; CM joint, carpometacarpal joint.

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also less invasive than intracortical electrode signals, ECoG has drawn attention as an effective brain recording for recent BMI. To the best of our knowledge, the prediction of three-dimensional finger motions using ECoG has not been realized yet.

We predicted extrinsic fingertip positions in three-dimensional space using ECoG signals recorded from the left hemisphere in an intractable epilepsy patient. The patient performed extension/flexion tasks with the thumb, index, and middle fingers of the right hand. Three-dimensional positions of the fingertips were measured with a motion capture system. The abduction and adduction motions were also observed, as well as flexion and extension motions. Ninety planar electrodes were implanted subdurally on the sensorimotor cortex. We estimated coordinates x, y, and z of fingertips from ECoG signals using the proposed ECoG feature extraction method and sparse linear regression. We also examined the prediction results with Pearson's correlation coefficient (CC) and normalized root-mean-square error (nRMSE).

2. Methods

2.1. Ethics statement

The study was approved by the ethics committee of Osaka University Hospital (Approval No. 08061) and performed in accordance with the Declaration of Helsinki. ECoG electrodes were implanted as part of the patient's medical treatment. Written informed consent was obtained prior to all research procedures. Written informed consent was also obtained for the use of the patient's data in the study.

2.2. Participant and implanted electrodes

A 20 year old female diagnosed with intractable epilepsy participated in this study. The patient showed no motor dysfunction. She was subdurally implanted with one 4×5, one 2×5, and two 5×6 electrode arrays (Unique Medical Co., Tokyo, Japan) on the left hemisphere, including the central and lateral sulci as shown in Fig. 1. The arrays were composed of planar platinum electrodes with a diameter of 3 mm and an inter-electrode distance of 10 mm. The arrays were implanted for two weeks to determine the locations of epileptic foci. ECoG signals were recorded at a sampling rate of 1000 Hz with a 128-channel digital EEG system (EEG 2000; Nihon Koden Corporation, Tokyo, Japan). ECoG signals were referenced to a scalp electrode on the nasion. Three example traces of raw ECoG signals are shown at the bottom of Fig. 1B, recorded at electrodes a, b, and c on the primary motor cortex (Fig. 1C).

2.3. Behavioral tasks and motion recordings

Behavioral tasks were performed approximately one week after surgery in an electromagnetically shielded room. The patient was seated in a chair with her right hand placed on a table palm-down. She performed three finger-tapping tasks 1, 2 and 3 (Fig. 1A) at her own pace for approximately 145 s for each task. Task 1 consisted of repeated extensions and flexions of the thumb, totaling 58 trials. Task 2 consisted of repeated index finger extensions and flexions, also totaling 58 trials. Task 3 consisted of middle finger extensions and flexions, totaling 54 trials. For all tasks, the wrist and non-task fingers remained stationary on the table. Each task was started after a verbal cue from the researcher. The onset of each trial was defined as the time point when tangential velocity at the fingertip exceeded 5% of the maximum velocity during the trial, while the end point of each trial was defined at 0.1 s before the next onset (the yellow box in Fig. 1B depicts an example ith trial). Coordinates x, y, and z of the wrist and tips of the thumb, index, and middle fingers were recorded with an optical motion capture system (Eagle Digital System; Motion Analysis Corporation, Santa Rosa, CA) at a sampling rate of 100 Hz using reflective 3D markers (black spheres in Fig. 1A). The relative coordinates of tips of the thumb and fingers with respect to the 3D marker on the wrist were used for trajectory prediction.

2.4. ECoG signal processing and decoding procedures

ECoG signals were pre-processed, and then trajectories of the tips of thumb and fingers were predicted from the ECoG signals using sparse linear regression (Sato, 2001). Details on this method can be found in our previous studies (Shin et al., 2012; Nakanishi et al., 2013). ECoG pre-processing and decoding are summarized as follows: (1) raw ECoG signals were re-referenced to a common average reference (CAR). (2) Re-referenced signals were filtered into nine frequency bands with 4th-order bandpass Butterworth filters: δ (0–4 Hz), θ (4–8 Hz), α (8–14 Hz), $\beta 1$ (14–20 Hz), $\beta 2$ (20–30 Hz), $\gamma 1$ (30–60 Hz), $\gamma 2$ (60–90 Hz), $\gamma 3$ (90–120 Hz), and $\gamma 4$ (120–150 Hz). (3) Each filtered signal was smoothed with a windowed low-pass filter (Kaiser window with filter length $n = 333$, parameter $\beta = 6.204$, transition bandwidth $\Delta f = 12$ Hz, and cut-off frequency $\omega_c = 8$ Hz) (Mitra, 1998). In the procedures (2) and (3), we bidirectionally filtered whole ECoG signals of each session forward first and then backward. (4) Smoothed signals were down-sampled from 1000 Hz to 100 Hz, i.e., the sampling rate of the motion capture. (5) Each signal was z-score normalized using its mean and standard deviation. (6) A weight matrix to be used for the trajectory prediction was obtained with sparse linear regression using a training set of finger trajectories and z-scores. A fingertip position at time t was expressed with 81,000 signal points (100 time points $\times$ 90 electrodes $\times$ 9 frequency bands) over the 1 s just before time t. The sparse linear regression was separately executed for each coordinate x, y and z in this study. The weight matrix (size $1 \times 81{,}000$) for each coordinate is independently decided. To shorten running time on a computer, it is possible to simultaneously obtain the weights of three coordinates as one matrix (size $3 \times 81{,}000$). However, the three rows in the matrix do not have direct relationship each other. (7) Finger trajectories were predicted from one trial of test data using the weight matrix. (8) Prediction accuracy was evaluated according to CC and nRMSE between the actual and inferred trajectories. (9) Steps (6)–(8) were repeated, applying each trial as test data one time to achieve the leave-one-out cross validation (LOO-CV), and then CC and nRMSE were averaged across all trials. Two-way ANOVA with Tukey's multiple-comparison test was adopted to test the effects of factors such as electrodes selected for prediction and the three coordinates.

3. Results

The patient performed finger-tapping tasks with the thumb (task 1), index finger (task 2) and middle finger (task 3) as shown in Fig. 1A. The average and standard deviation of the duration of trials in tasks 1, 2, and 3 were 2.21 ± 0.23, 2.21 ± 0.22, and 2.36 ± 0.25 seconds, respectively. Of the 54–58 trials per task, 14, 15, and 11 trials for tasks 1, 2, and 3, respectively, were excluded from the LOO-CV due to burst noise in the ECoG signals.

Fig. 2A shows all results of the predicted trajectories using 90 electrodes. Fingertip trajectories with different spatial directions were successfully decoded from ECoG signals. Mean and the standard error of the mean (SEM) of CC values across all trials and coordinates for the thumb, index, and middle fingers were 0.89 ± 0.0069, 0.86 ± 0.0098, and 0.86 ± 0.0088, respectively. nRMSE means and SEMs for the thumb, index, and middle fingers were 0.30 ± 0.016, 0.38 ± 0.028, and 0.28 ± 0.0078, respectively. Typical examples of each finger trajectory with CC and nRMSE