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Robust, long-term control of an electrocorticographic brain-computer interface with fixed parameters

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All previous multiple-day brain-computer interface (BCI) experiments have dynamically adjusted the parameterization between the signals measured from the brain and the features used to control the interface. The authors present the results of a multiple-day electrocorticographic (ECoG) BCI experiment.

A patient with a subdural electrode array implanted for seizure localization performed tongue motor tasks. After an initial screening and feature selection on the 1st day, 5 consecutive days of cursor-based feedback were performed with a fixed parameterization. Control of the interface was robust throughout all days, with performance increasing to a stable state in which high-frequency ECoG signal could immediately be translated into cursor control.

These findings demonstrate that ECoG-based BCIs can be implemented for multiple-day control without the necessity for sophisticated retraining and adaptation. *(DOI: 10.3171/2009.4.FOCUS0977)*

Key Words • **brain-computer interface** • **motor cortex** • **feedback** • **stability** • **control**

Human neocortical activity is dependent upon a wide variety of interdependent parameters. Across different spatial and temporal scales, this has been associated with a nonstationary neural signature in experimental recording. Attempts to capture and translate this neural activity as a control signal in a BCI have, to date, all relied upon dynamic decoding algorithms that either adapt continuously or are recalibrated between experimental runs.

Brain-computer interfaces translate cortical signals for device control, bypassing the peripheral nervous system and motor pathways, and directly coupling neural activity in the CNS to a computational device for communication or manipulation of virtual and physical devices. Some common recording methods that researchers have used to capture neural activity have been to record the electric potential from extracranial EEG, cortical surface ECoG, and single-unit electrode recording using penetrating electrodes.[18] Regardless of recording technique, devices that replace natural control pathways will have to be robust over very long timescales.

To detect and localize a specific control signal for the purposes of a BCI, a neural feature which is correlated with intent, and which can be volitionally modified, must be identified. The translation of the brain signal to a reliable control feature is characterized by some parameterization. An appropriate set of parameter values are typically learned during a controlled behavioral screening and updated using continual adaptation or repeated screening. Wolpaw et al.[28] proposed the idea of 2 levels of training and adaptation of a BCI system. In the first level, the BCI system initially adjusts to the user and then remains fixed for the duration of control. Unfortunately, many cortical recording techniques have been found to show large variation both within and across experimental sessions.[7,8,13,14,27] Wolpaw suggested a second level of adaptation was required that contained multiple online adjustments to account for and adjust to variation within a single experimental session. Other researchers have performed long-term experiments in which the translation parameters were not adjusted during the online experimental period, but parameterization values were relearned prior to each online experimental session.[5,16,29]

Electroencephalography, the acquisition of cortical potentials from the surface of the scalp, allows long-term data acquisition of human cortical signals at the expense of spatial resolution. Guger et al.[4] proposed that an appropriate method for an EEG-based BCI is an adaptive autoregressive approach to parameter estimation, based upon changes in spectral power, and many EEG BCI re-

Abbreviations used in this paper: BCI = brain-computer inter–face; ECoG = electrocorticography; EEG = electroencephalography; PSD = power spectral density.

search groups use this autoregressive estimation to isolate features for acceptable control of EEG systems.[6,17,27] This approach was used by Shenoy et al.,[22] who performed closed-loop control of an EEG system with control parameters found using training data. Because of the intrinsic discrepancy between training and online data, they found that an adaptive control algorithm was necessary for accurate classification.

"Single-unit" recordings use penetrating intracortical electrodes to record spike events from one or a few neurons adjacent to the electrode tip. They have been used successfully to extract features for feedback in primates[1,21,23] and humans,[5] but in all cases the parameterization required adaptive algorithms that modified the control parameters in real time. In primate studies, Donoghue et al.[21] used coadaptive constant-parameter prediction, whereas Fetz[3] and Wessberg et al.[25] used artificial neural networks that adapted to changes in spike rates during online control· to attain viable levels of classification. Furthermore, both cases required novel control-parameter selection prior to each experimental session. The long-term single-unit BCI experiments in humans performed by Hochberg et al.,[5] over a 9-month period, required relearning of control parameters before each of 57 consecutive recording sessions.

Schwartz and colleagues have recently demonstrated the ability to record neural spikes from an intracortical microelectrode array implanted in the proximal arm region of monkey primary motor cortex and use these recordings to control a prosthetic arm in 3 dimensions for the purpose of self-feeding.[24] Though the monkey was able to gain control over the arm, a training period consisting of 4 iterations of control-parameter calibration was required at the beginning of each daily session. Control parameters from the final training estimation were used by the expectation-maximization algorithm used for control throughout the remainder of the day.

Electrocorticography, in turn, requires invasive placement of an electrode array subdurally to record cortical potentials at a higher spatial resolution, and thus a more local neuronal population, than EEG. Electrocorticography arrays have been successfully used to control a BCI device in 1 dimension[8,9] and recently in 2 dimensions.[20] Both control paradigms have used adaptive algorithms that updated control parameters during closed-loop control. The short duration of these trials, due to the clinical needs of the subjects enrolled in these studies, has prevented investigation of the day-by-day variability of the classification parameters.

We demonstrate that, using anatomically intuitive feature localization and a robust high-frequency signal ("χ-band"[11]) from the electrocorticogram, continuous control using fixed parameters is possible without retraining, relearning of parameters, or continuous parameter adaptation over 5 consecutive days of robust control of a BCI.

Methods

Patient Characteristics

The patient in our ECoG study was a 32-year-old man who was being treated at Harborview Hospital at the University of Washington for intractable epilepsy, refractory to medical therapy. The patient underwent implantation of a subdural electrode array above the right frontotemporal cortex to localize the seizure focus during a 7-day monitoring period. The postoperative radiograph was used to determine the electrode grid locations.[12] Informed consent was given by the patient in accordance with University of Washington Institutional Review Board protocol.

Signal Acquisition

The implanted ECoG array contained platinum electrodes in an 8 × 6 rectangular formation. Electrode contacts were circular (4 mm in diameter, 2.3 mm exposed) and embedded in Silastic with a face-center spacing of 1 cm. After leaving the head, the signals were split into 2 paths: one into the clinical monitoring system and the other into a SynAmp 2 (Compumedics Neuroscan) recording system. The amplified signals were passed to the general-purpose BCI2000 software suite. Samples were taken at 1000 Hz and band pass filtered from 0.3 Hz to 200 Hz. Since the sampling rate and filtering settings were much greater than the range used for control in this trial (80–100 Hz), the Nyquist frequency considerations did not impact the findings and filtering artifacts were not present. The BCI2000 software suite[19] was used for stimulus presentation, data acquisition, and real-time processing.

Study Tasks

The study consisted of an initial screening for control features, and then a 5-day repeated BCI feedback experiment. The initial screening was a simple cue-based movement task to identify an appropriate electrode-frequency band combination for cursor control. In this task, a 3-second visual word cue was given to move either the tongue (the word "tongue" displayed on the screen) or the hand ("hand"). During the cue presentation, the patient would repeatedly open and close his left hand 3–4 times or protrude and retract his tongue 3–4 times. Thirty cues of each type were interleaved in random order, with 3-second rest periods (blank screen) after each cue. An appropriate frequency range–electrode combination for feedback (80–100 Hz, in 2 electrodes, at Talairach coordinates [58, 13, 28] and [58, 4, 33]) was chosen by comparing the distributions of power at each frequency, in each electrode, during "tongue" cues with the corresponding distribution from rest cues (quantified using the squared cross-correlation coefficient, r^2, associated with the comparison). The power in this frequency range–electrode combination was then coupled to the movement of a cursor in a cursor-based BCI experiment.[2,8–10,18,26] Due to the lack of electrode coverage over the hand motor cortex area, no significant difference in power distributions was present between "hand" cues and rest cues, and thus hand motor cortex was not chosen as a control feature for the BCI task. The velocity of the cursor, $\dot{y}$, was determined by the relation $\dot{y} = g[P(t) - P_0]$, where $P(t)$ denotes the power between 80–100 Hz in the electrode at Talairach coor-

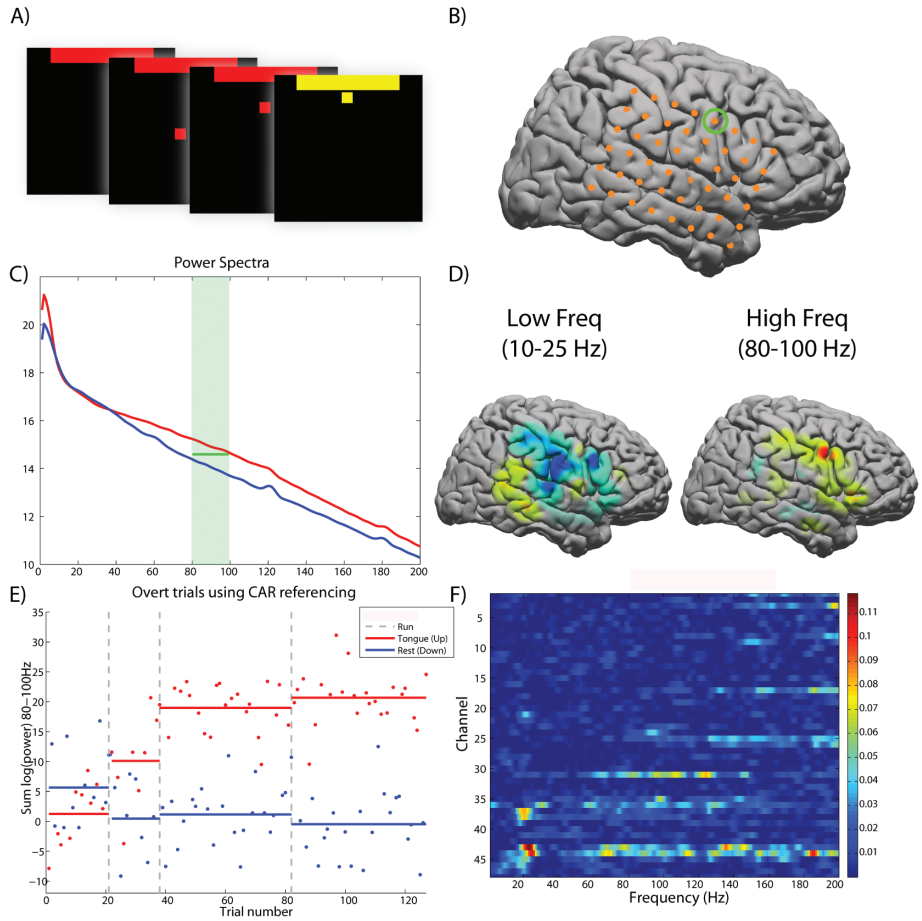

Fig. 1. A: Cursor control task. A sequence of screenshots illustrating a successful trial: The patient was able to drive the square cursor toward the rectangular goal region. B: Standardized brain image showing electrode locations superimposed as *orange dots.* The electrode used for control is indicated by the *green circle.* C: Linear feature found during screening for Electrode 44 (*green circle* in B). The *blue trace* shows the power spectral density during rest; the *red trace* shows the movement spectra. The *green line* within 80–100 Hz is the threshold set on the 1st day; it was not modified during the 5-day recording session. Note the broad spectral shift within the χ band (75–150 Hz). D: Cortical plots of low- and high-frequency power, showing a broad decrease in power at low frequencies and a localized increase at high frequencies. Freq = frequency. E: Graph illustrating the results of 4 overt cursor control runs, showing the learning curve during the 1st day. The second run showed significant differences in the control feature at a level of $p < 0.05$ and the final 2 runs at $p < 0.001$. Tongue (Up) indicates the tongue task was being performed, causing the cursor to move up on the screen; Rest (Down) indicates that the patient's tongue was at rest, allowing the cursor to move down. Abbreviation: CAR = Common Average Referencing. F: An r2 plot of frequency versus channel for an imagined control trial. High frequency band activity can be seen from 60 to 200 Hz on a number of channels, including the control Channel 44.

dinates [58, 13, 28] and [58, 4, 33] (Fig. 1B). P_0 denotes a "mean" value (Fig. 1C), above which the cursor moved up, and below which, the cursor moved down. The gain, g, was chosen so that the cursor would move in a reasonable range. The parameters P_0 and g were not changed throughout the task. For each target trial during the BCI experimental runs, the subject was presented with a cursor in the center of the screen and a target at either the top or bottom of the screen (Fig. 1A). When the patient imagined moving or actually moved his tongue, the cursor would be driven upwards and when the patient was at rest, the cursor would move downward (according to the relation above). If the cursor was successfully directed to the target or 7 seconds elapsed without cursor/target collision, the trial was reset and a new target was presented. Target locations at the top or bottom of the screen were presented in randomized order, but in roughly equal number during each experimental trial. A set of 40 consecutive, randomized target presentations ("trials") were performed during an experimental run. Specific instructions were given to imagine the kinematics of the movement ("kinesthetic imagery"[15]). Sublingual differential EMG was used to verify that there was no muscle movement during the imagery-based experimental runs.

Offline Analysis

The signal was re-referenced to the common average potential across all electrodes at each sample. The data were then segmented into blocks from 3 types of periods: when the upper target was presented, when the lower target was presented, and when no target was presented. The power spectral density (PSD) for each block was calcu-

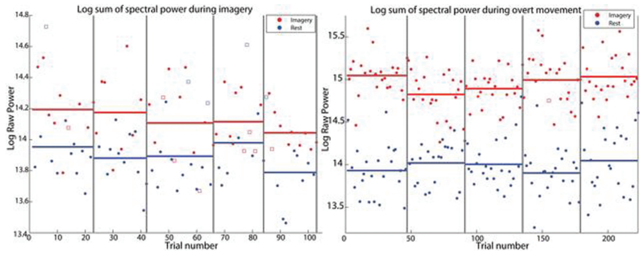

FIG. 2. Graphs showing results of final control trials for imagery and overt movement. *Points* represent total power within the control band for each individual run during the final trial across 5 days. *Vertical bars* indicate separate days; *horizontal bars* represent the geometrical mean for all runs each day. Failed runs (those in which the target was not reached by the cursor) are shown as *squares.* For both movement and imagery tasks, an increase in power can be seen for all runs during the tasks *(red)* in comparison with the runs during runs *(blue).* All trials showed significant differences in the control feature at a level of $p < 0.001$ (bootstrap 105 iterations, comparing mean power between movement/imagery target trials versus rest target trials).

lated using Welch's averaged periodogram method with the fast Fourier transform and a Hann windowing function. The length of data for the FFT was a 1000-sample window, and windows were overlapped by 900 msec. The spectra from each block were normalized by dividing through by the mean power across all blocks (of all types combined) at each frequency (effectively whitening the spectra), and then the log of the summed values across the 80–100 Hz range were determined as shown in the figures.

Online Control

For each electrode in the grid, we continuously calculated the voltage PSD using an autoregressive technique[9] for frequencies between 0 and 200 Hz (binned at 2 Hz) for each trial and for the rest periods between trials. The PSD was calculated from the previous 280 msec of data, every 40 msec. Cursor velocity was calculated by comparing the power between 80 and 100 Hz in electrodes at Talairach coordinates [58, 13, 28] and [58, 4, 33]. The position was then updated according to $\dot{y} = g[P(t) - P_0]$, as described above.

Results

After the initial learning trial (during which the difference in power within the control band was significant at $p < 0.01$), the results of every subsequent overt trial were statistically significant at $p < 0.001$. For each session, bootstrapping was performed for 10^5 iterations on the mean power during activity and rest for each run. All power values for each day were combined and a random permutation of the powers was selected for both activity and rest. The difference between the bootstrapped means was compared with the original distribution's difference in means resulting in a p value calculated according to $p = 1 - (n/N)$, where N is the total number of bootstrap iterations and n is the number of bootstraps in which the difference in means was smaller than the 2 initial distributions.

During all but one overt trial, target accuracy was 100%; accuracy during the remaining trial was 97.5%. Once control was demonstrated with overt control, imagery tasks were performed. Due to the nature of the imagery task, it is not possible to ensure that every run or trial is performed in the exact same manner for each run. The final run of imagery-based feedback for each day during imagery (Fig. 2) showed significant ($p < 0.001$, bootstrap 10^5 iterations) control, with accuracies of 20/2 (hits/misses), 19/0, 19/5, 14/4, and 17/2, compared with a random chance accuracy of 50/50.

Discussion

All previous BCI studies have used some form of an adaptive algorithm. In this study, however, we have demonstrated that extended control of a simple ECoG-based BCI is possible with fixed parameters for a 5-day period, without recalibration, adaptation, or retraining. This suggests that the high-frequency ECoG signal is robust across several days. This phenomenon could not be explored in previous ECoG studies[2,7,8,18,26] because of the limited time with this patient population. This finding suggests that ECoG-based BCIs can be implemented in a population of impaired patients (with conditions such as paralysis, stroke, or amyotrophic lateral sclerosis) for the purpose of prosthesis development. Furthermore, recent studies have demonstrated the potential to extract several simultaneous control signals from an ECoG array.[20]

For any long-term BCI applications such as prosthetic limbs, it is important that the neural signals used for control be robust and remain spatially and frequency-range stable over a long period of time. Relearning control parameters before every use of BCI applications may not be realistic or feasible, thus a signal that is robust and stable over long periods of time would be an ideal candidate for a control feature. Spatially distinct features on the cortex (for example, tongue and hand motor) can be combined to add multiple degrees of robust, stable control from ECoG. Future studies will investigate intuitive mappings of changes in the cortical power spectra to different modalities of control of a prosthetic limb, including individual joint angle modulation and linear/nonlinear grip pose synergies. Additional research into whether the current binary output can be mapped to a scalar domain would aid in applying ECoG signals to these types of applications.

Conclusions

We have shown that it is possible to select a control feature in the χ-band range that is stable and robust over a long period of time, suggesting the χ-band is an appropriate range to use for long-term ECoG BCI applications.

Disclosure

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