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A Case Study on the Relation Between Electroencephalographic and Electrocorticographic Event-Related Potentials

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Abstract— **This study presents a preliminary analysis of the relationship between electroencephalographic (EEG) and electrocorticographic (ECoG) event-related potentials (ERPs) recorded from from a single patient using a brain-computer interface (BCI) speller. The patient had medically intractable epilepsy and underwent temporary placement of an intracranial ECoG grid electrode array to localize seizure foci. The patient performed one experimental session using the BCI spelling paradigm controlled by scalp-recorded EEG prior to the ECoG grid implantation, and one identical session controlled by ECoG after the grid implantation. The patient was able to achieve near perfect spelling accuracy using EEG and ECoG. An offline analysis of the average ERPs was performed to assess how accurately the average EEG ERPs could be predicted from the ECoG data. The preliminary results indicate that EEG ERPs can be accurately estimated from proximal asynchronous ECoG data using simple linear spatial models.**

I. INTRODUCTION

A Brain-computer interface (BCI) is a system that allows individuals with severe neuromuscular disorders to communicate and control devices using their brain waves [1]. One of the most promising signals for controlling a BCI are event-related potentials (ERPs) such as the P300. The P300 is an evoked response to an external stimulus that has been traditionally observed in scalp-recorded electroencephalography (EEG). The scalp-recorded P300 response and constituent ERPs have proven to be reliable signals for controlling a BCI using the P300 Speller paradigm [2]. Based on multiple studies in healthy volunteers [3][4][5], and initial results in persons with physical disabilities[6][7][8], the P300 Speller has the potential to serve as an effective communication device for persons who have lost or are losing the ability to write and speak.

Electrocorticography (ECoG), electrical activity recorded directly from the surface of the brain, has also recently been demonstrated to be viable for controlling the P300 Speller[9]. Because ECoG electrodes are closer to the source of the desired brain activity, ECoG has been shown to have superior signal-to-noise ratio, and spatial and spectral characteristics compared to EEG [10][11][12], which will inevitably provide superior BCI performance. However, unlike EEG, ECoG requires surgical implantation, and much work must be done in terms of validating chronic implantations and establishing long-term efficacy before it will be a practical BCI alternative for patients.

The skull and scalp tissue act as a volume conductor for the brain's electrical activity [13], thus it is conceivable that scalp recorded EEG can be represented as a linear mixture of underlying ECoG signals. Since there are several major issues with simultaneous recording EEG and ECoG in temporarily implanted humans, such as the effect of the incision and ECoG implantation trauma on simultaneously monitored EEG, the approach taken for this analysis compares EEG data recorded pre-ECoG grid implantation and ECoG data recorded after implantation. Essentially, the averaged ERPs, which are assumed to be consistent and time-invariant for EEG and ECoG, are used for the modeling. It is hypothesized that accurate models of EEG constructed from ECoG will provide a better understanding of sources of scalp-recorded ERPs and the electrical transmission characteristics of the skull and surrounding tissue, eventually leading to more effective EEG-based BCI processing techniques. This preliminary work merely presents a case study of mathematical modeling EEG from ECoG.

II. METHODOLOGY

A. Patient Information

The data were collected from a patient (27 year old male) with medically intractable epilepsy who underwent Phase 2 evaluation for epilepsy surgery with temporary placement of an intracranial grid electrode array to localize seizure foci prior to surgical resection. The patient exhibited specific impairments in word finding, attention, processing speed, and learning efficiency. The patient was evaluated to be in the borderline to mildly deficient range for intellectual functioning. The patient was presented at Mayo Clinic Florida's multidisciplinary Surgical Epilepsy Conference where the consensus clinical recommendation was for the patient to undergo invasive monitoring primarily to localize the epileptogenic zone. The study was approved by the Institutional Review Board of both Mayo Clinic and the University of North Florida. The patient gave informed consent.

The patient's seizure onset zone was determined to reside in the left hippocampus. A 36-contact ECoG grid was placed over the left frontal-parietal region and two depth electrodes were placed in the left hippocampus (see Figure 4 for approximate electrode positions). Electrode placements and duration of ECoG monitoring were based solely on the requirements of the clinical evaluation, without any consideration of this study. The patient had post-operative anteriorposterior and

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lateral radiographs to verify electrode locations. After electrode implantation, the patient was admitted to an ICU room with epilepsy monitoring capability. Clinical ECoG data were gathered with a 64-channel clinical video-EEG acquisition system (Natus Medical, Inc.; CA, USA).

B. BCI Data Acquisition

Prior to electrode implantation, the patient performed a single BCI session using scalp-recorded EEG. The EEG was recorded using an ElectroCap International cap with 32 electrodes distributed over the scalp, based on the International 10-20 system (see Figure 1). The EEG was amplified, bandpass filtered 0.5-500 Hz, and digitized at 1200 Hz using two 16-channel g.USB amplifiers. The high sampling rate was selected to be consistent with the ECoG data collection. Stimuli were presented and the EEG data were recorded using BCI2000, a general-purpose BCI system [14].

Additionally, the patient performed one BCI session using ECoG. This testing occurred approximately 48 hours after electrode implantation. Testing was performed only when the patient was clinically judged to be at cognitive baseline and free of physical discomfort that would affect attention and concentration. Testing was performed at least six hours after a clinical seizure. The 32-channel subset of ECoG electrodes used for the BCI experiments is shown in Figure 4, with the approximate grid location with respect to the scalp electrodes is indicated by the circumscribed region in the upper topography. All electrodes were referenced to a scalp vertex electrode and recorded using the identical hardware, software, and protocols as the EEG data collection. The signals for the BCI experiments were acquired concurrent with the clinical monitoring via a 32-channel electrode splitter box.

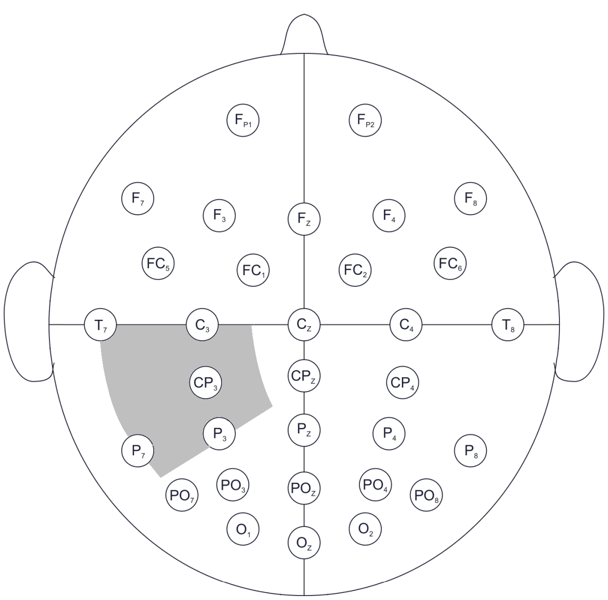

Fig. 1. The 32-channel EEG electrode montage used in the study. The gray area indicates the approximate location of the ECoG grid.

C. Task, Procedure, and Design

The experimental protocol was based on the protocol used in an EEG-based P300 Speller study [3], and was consistent for both the EEG and ECoG session. The patient sat in a comfortable chair (for EEG) or hospital bed (for ECoG) about 75 cm from a video monitor and viewed the matrix display as shown in Figure 2. The task was to focus attention on a specified character in the matrix and silently count the number of times this target character flashed, until a new character was specified for selection. All data was collected in the copy speller mode: words were presented on the top left of the video monitor and the character currently specified for selection was listed in parentheses at the end of the character string as shown in Figure 2. Each session consisted of 8-11 experimental runs of the P300 Speller paradigm; each run was composed of a word or series of characters chosen by the investigator. This set of characters spanned the set of characters contained in the matrix and was consistent for each session. Each session consisted of between 32-39 character epochs. A single session lasted approximately one hour. One complete EEG session and one complete ECoG session were collected from the patient.

Fig. 2. The P300 Speller in Copy-Spell mode, with on-screen feedback. This mode prompts the user to spell a predefined word, in this case DICE.

D. Data Analysis

The patient achieved perfect online performance after 15 flash sequences with both EEG and ECoG as shown in Figure 3, using a distinct static classifier for each case (refer to [3] for details regarding ERP classification). Thus, it is presumed that the patient produced consistent ERPs across both conditions. For reference, Figure 4 illustrates the topographic correlation of the EEG and ECoG ERP amplitudes with the target stimuli.

The models were exclusively constructed using the target stimulus ERPs (resulting from a flash that the subject was instructed to attend) because they represent consistent and predictable evoked neural activity, as opposed to the non-target stimulus data that primarily consist of spurious background activity.

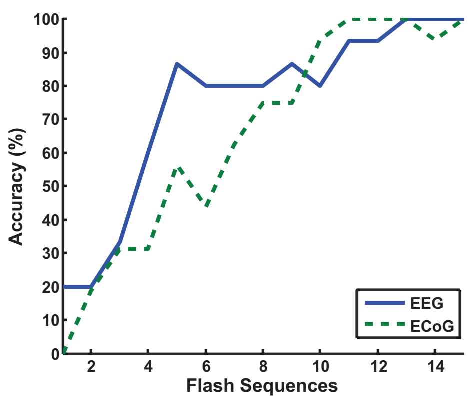

Fig. 3. The character prediction accuracy with respect to the number of flash sequences. Note that the online accuracy (after 15 sequences) was 100%.

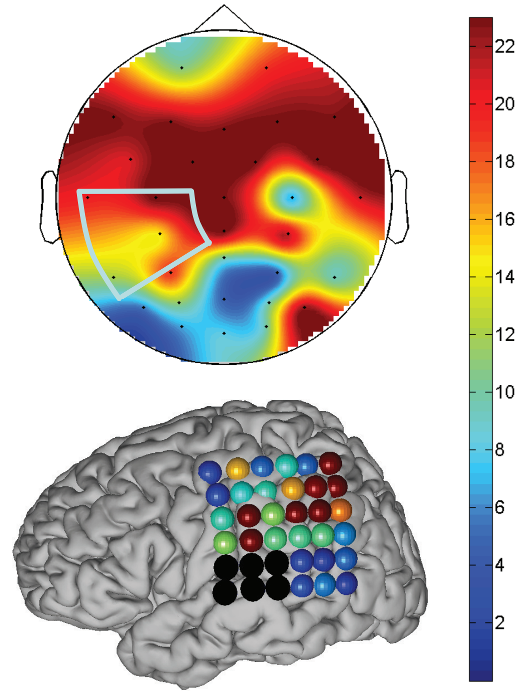

Fig. 4. The topographic correlation of the EEG (top) and ECoG (bottom) ERP amplitudes with the target stimuli. The circumscribed region in upper figure indicates the approximate location of the ECoG grid. The scale corresponds to the electrode coloring and indicates the maximum -log(p-value) over the 800 ms interval for the particular electrode, where the p-value tests the hypothesis that the correlation between the amplitude and the target stimuli is zero.

All data were lowpass filtered to 20Hz and decimated to 240Hz, to smooth the data while retaining sufficient samples for modeling and ERP visualization. For each EEG and ECoG channel, 800-ms segments of data following each flash were extracted as the ERP. The average target ERP was computed to form the archetype ERP for each EEG channel. The first half of the ECoG target ERPs (480 ERPs) were averaged for each channel and used in an ordinary least-square linear regression model to predict each archetype ERP, equivalently producing a spatial filter based on all ECoG channels for predicting each EEG channel's archetype ERP. The second half of the ECoG ERPs were used to validate the EEG archetype prediction for each channel by computing the mean-squared error (MSE) between the predicted ERP and the archetype ERP. First, each archetype ERP was scaled to have unit variance. The same scale factor was applied to the respective ECoG predicted ERP. This was done in order to compare the MSE across channels.

III. RESULTS

Figure 5 shows the MSE for the predicted ERPs at each EEG channel. Figure 6 shows the archetype and the predicted ERPs for selected channels, as well as the corresponding ECoG spatial filter that produced the predicted ERPs.

IV. DISCUSSION

The results show that the archetype EEG ERPs can be accurately modeled using a linear combination of spatial ECoG ERPs obtained from a separate experimental session. These models also generalize to independent data. The spatial filter weights shown in Figure 6 indicate that relatively few ECoG channels contribute to the predictions, and in most cases the contributing ECoG electrodes are positioned directly under or in close proximity to the respective EEG electrode, as would be expected. For instance, the three most relevant electrodes for CP_3 are grouped very near the scalp electrode. However, it is also interesting to note that the highest magnitude electrode weights are not always positioned directly under or spatially congruent to the respective EEG electrodes. This could be an artifact of the regression due to the relatively small amount of data used to construct the average responses. Although only the EEG electrodes adjacent to the ECoG grid are presented, several other EEG ERPs were predicted accurately. This is likely due to the volume conduction properties of the skull and surrounding tissue.

With regard to the classical P300 electrodes (Fz, Cz, and Pz) and the relevant electrodes used in online classification shown in Figure 4, the ECoG grid was not optimally positioned. Nevertheless, there is significant overlap between the relevant classification electrodes for EEG and the EEG predictions that produced a low MSE. It is also interesting to note that there doesn't appear to be much overlap between the relevant classification electrodes for ECoG and the relevant ECoG spatial filter weights for predicting the EEG. However, the relevant classification electrodes for ECoG as presented in Figure 4 were evaluated in isolation; it was found that nearly all of the ECoG electrodes contributed to the online classifier.

Although the online performance of ECoG and EEG was comparable, it is believed that the superior ECoG signal characteristics can provide improved performance under the proper conditions. For example, there are several factors that likely disadvantaged the ECoG performance such as the patient's underlying condition and post-surgery physical and mental state, and the suboptimal, localized ECoG electrode

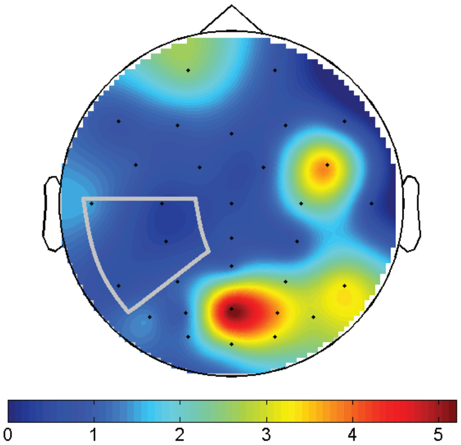

Fig. 5. The MSE for the predicted ERPs at each EEG channel. The circumscribed region indicates the approximate location of the ECoG grid.

coverage compared to EEG. With greater EEG and ECoG coverage, it may be possible to generate inverse models that would better localize the relevant ECoG activity from EEG. The resulting EEG spatial filters could conceivably improve EEG-based BCI performance.

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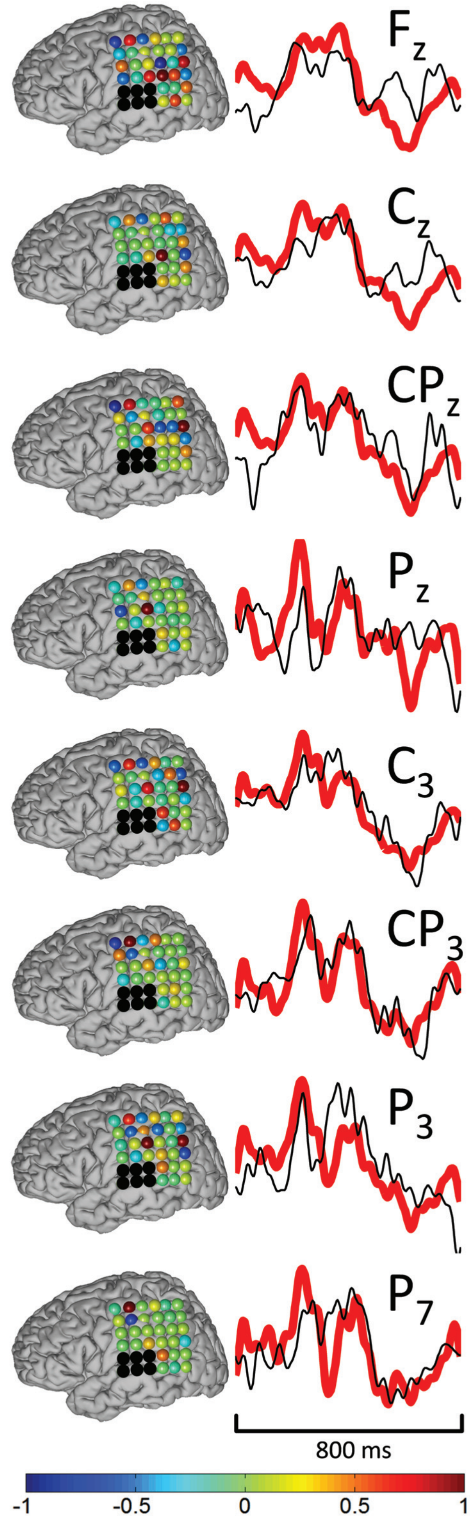

Fig. 6. Right Column: The archetype EEG ERPs (red) and the predicted ERPs (black) for selected EEG channels. Channels Fz, Cz, and Pz represent the classical P300 electrodes, while the other electrodes are positioned adjacent or directly over the ECoG grid. Left Column: The corresponding ECoG spatial filter weights that generated the predicted ERPs. The colorbar indicates the relative scale for the spatial filter weights. Note that the black ECoG electrodes were not used for BCI recording due to hardware channel limitations.