Published in final edited form as:

Clin Neurophysiol. 2013 July ; 124(7): 1321–1328. doi:10.1016/j.clinph.2013.02.002.

Improved P300 speller performance using electrocorticography, spectral features, and natural language processing

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Abstract

Objective—The P300 speller is a system designed to restore communication to patients with advanced neuromuscular disorders. This study was designed to explore the potential improvement from using electrocorticography (ECoG) compared to the more traditional usage of electroencephalography (EEG).

Methods—We tested the P300 speller on two epilepsy patients with temporary subdural electrode arrays over the occipital and temporal lobes respectively. We then performed offline analysis to determine the accuracy and bit rate of the system and integrated spectral features into the classifier and used a natural language processing (NLP) algorithm to further improve the results.

Results—The subject with the occipital grid achieved an accuracy of 82.77% and a bit rate of 41.02, which improved to 96.31% and 49.47 respectively using a language model and spectral features. The temporal grid patient achieved an accuracy of 59.03% and a bit rate of 18.26 with an improvement to 75.81% and 27.05 respectively using a language model and spectral features. Spatial analysis of the individual electrodes showed best performance using signals generated and recorded near the occipital pole.

Conclusions—Using ECoG and integrating language information and spectral features can improve the bit rate of a P300 speller system. This improvement is sensitive to the electrode placement and likely depends on visually evoked potentials.

Significance—This study shows that there can be an improvement in BCI performance when using ECoG, but that it is sensitive to the electrode location.

Keywords

brain-computer interface; electrocorticography; event-related potential; P300; speller; natural language processing

1. Introduction

Brain Computer Interfaces (BCI) are systems designed to restore functionality to victims of high brain stem injury or severe neuromuscular disease such as amyotrophic lateral sclerosis (ALS). A BCI system reads the electrical signals in the brain and translates them into computer commands (Wolpaw et al. 2002). A computer can then convert these commands into actions such as typing text (Farwell and Donchin, 1988), moving a cursor (Wolpaw et al., 1991), or controlling robotic prosthetics (Lauer et al., 2000; Pfurtscheller et al., 2000). While restoring communication in completely locked-in patients has not yet been demonstrated, it has been shown to be possible in all other stages of paralysis (Kübler et al. 2008).

The P300 speller is an example of a BCI system designed to restore communication by translating cortical signals into simulated keyboard input (Farwell and Donchin, 1988). The system contains a graphical interface consisting of a grid of alphanumeric characters that are periodically illuminated in a pseudo random manner. The user's task is to focus on one target character that he wishes to select. When the attended character is intensified, a response signal is evoked in the user's electroencephalogram (EEG). The system detects these evoked responses and selects the character that was flashed in the associated stimuli. In order to compensate for low signal to noise ratio, several trials are combined before a decision is made on a character. The need for repeated measures results in significant performance inefficiencies. Various improvements have been implemented that have resulted in real-time results ranging from 79–91% accuracy at 13–42 seconds per selection (Serby et al., 2005; Sellers et al., 2006, 2010; Lenhardt et al., 2008; Nijboer et al., 2008; Guger et al., 2009).

Since the main use of the P300 speller has been for communicating language, there have been recent studies that exploited knowledge about the language domain in order to improve the system's performance. Ryan et al. used dictionary lookups for strings of selected characters to add suggestions for word completion to the character matrix (Ryan et al. 2011). Speier et al. uses a Natural Language processing (NLP) algorithm that uses a model of the structure of real language to give higher prior probabilities to characters that are more likely to occur based on the context (Speier et al. 2012).

Recent studies have suggested that electrocorticography (ECoG) signals could be used in BCI communication due to its increased signal-to-noise ratio, high spatial resolution, and superior spectral content (Leuthardt et al., 2004, Wilson et al., 2006, Brunner et al., 2009, Miller et al., 2010). The obvious drawback of using implanted electrodes is that it requires invasive surgery. Still, a recent survey suggests that this surgery might be acceptable to some ALS patients if it yields sufficiently better performance (Huggins 2011). 61 people suffering from ALS were interviewed about BCI and 72% said that they would consider outpatient surgery and 41% would accept a short hospital stay in order to have an implanted BCI, but that current BCI systems do not yet achieve desired performance levels.

Two groups have already shown promising results in using ECoG in P300 speller studies. Brunner et al. conducted a study consisting of a single patient with a temporal grid and a six electrode strip in the occipital region (Brunner et al., 2011). Their analysis focused on the occipital strip and they reported accuracies approaching 100% after only 3 sets of flashes. Krusienski and Shih reported results from 6 subjects with varying electrode placement, mainly in the temporal and parietal cortices (Krusiensi and Shih, 2011a). The results of their subjects varied, but they generally showed a marginal improvement over EEG-based performance. Perhaps more interestingly, Krusienski and Shih also reported a significant correlation between the stimulus and spectral components of the response signal in ECoG

(Krusienski and Shih, 2011b). They did not however go as far as using spectral features in classification to determine if they can supplement temporal features and improve accuracy. Given that the detection and classification of P300 speller signals have traditionally focused on cortical signals in the time domain, further work characterizing spectral domain features is critical in understanding their potential value in target classification.

The goal of this study is to investigate factors that may modulate system performance in an ECoG-based BCI system, including spatial, temporal, and spectral factors. Two subjects with subdural implanted electrodes were tested using the P300 speller. Neither of these patients had electrodes implanted in the parietal cortex, so the actual P300 signal could not be detected. Instead, more general event-related potentials (ERP) including visually evoked potentials (VEP) were observed. Offline analysis was performed to determine the accuracy and bit rate that these subjects can achieve using this system to spell common 5 letter words both with and without integration of spectral features and NLP algorithms that could potentially further augment observed performance (Speier et al., 2012). Their results were compared to a dataset of 6 EEG subjects used in a previous publication (Speier et al., 2012). Spatial analysis was also performed to determine the cortical locations with the best classification ability for this task, showing possible optimal electrode placement for an invasive “P300” speller system.

2. Methods

2.1 Subjects

The subjects in this study had temporary subdural electrode arrays implanted to localize seizure foci prior to surgical resection. Both had corrected to normal vision and consented through protocol approved by the UCLA Institutional Review Board.

The first subject was an 18 year old left-handed male with seizures localized to the left occipital region. The patient had a 20-electrode grid implanted in the left lateral occipital region as well as subdural electrode strips implanted in the temporal (8 electrodes), anterior basal occipital (4 electrodes), mid basal occipital (4 electrodes), posterior basal occipital (6 electrodes), and occipital interhemispheric (6 electrodes) regions for a total of 48 electrodes (Figure 1a–b).

The second subject was a 45 year old right-handed female with seizures that were not localizable, but predominant in the right temporal region. The patient had a 32-electrode temporal parietal occipital grid. There were also electrode strips implanted in the suprasylvian (7 electrodes), anterior temporal (7 electrodes), middle temporal basal (4 electrodes), middle posterior temporal basal (7 electrodes), posterior temporal basal (7 electrodes), and occipital basal (8 electrodes) regions of the right hemisphere for a total of 72 electrodes. The anterior temporal and middle temporal basal strips were omitted because our amplifier was limited to 64 channels, resulting in a total of 61 electrodes used in our analysis (Figure 1c–d).

2.2 Data Collection

ECoG signals were recorded using four 16-channel g.USBamp amplifier systems (g.tec, Graz, Austria). Data was collected simultaneously with clinical monitoring by connecting the ECoG cables to a splitter at the time of implant. We could then connect our system to the splitter to acquire ECoG signals without interrupting the clinical monitoring system. Data was collected at 2400 Hz for the first subject and 512 Hz for the second and both were downsampled to 40 Hz for time-domain analysis. A notch filter at 60 Hz was used for both subjects. BCI2000 was used for data acquisition and experimental design (Schalk et al., 2004).

2.3 Experimental Paradigm

The system used a 6×6 character grid with row and column flashes, 50 ms flash duration, and 3.5 s pauses between selections. The first subject had an inter-stimulus interval (ISI) of 150 ms while the second had an ISI of 140 ms (as constrained by BCI2000 based on sampling rates). Each subject underwent three trials consisting of spelling a five letter word (subject 1: “HOUSE,” “BATCH,” and “ALOHA”; subject 2: “AVOID,” “BEING,” and “MIXED”) with 10 sets of 12 flashes (six rows and six columns) for each letter. The choice of target words for this experiment was independent of the NLP algorithm’s language model.

Both subjects were sitting upright in their beds in the UCLA epilepsy monitoring unit during the experiment. The stimuli were presented on a monitor that was on a cart next to the bed. The cart was positioned so that the subjects could look directly at the monitor with minimal head movement at a distance of approximately one meter.

This paradigm was designed to match the conditions used in the experiment by the Speier, et al. (2012) EEG study as closely as possible. That study used BCI2000 to record EEG signals from six healthy subjects using the P300 speller to type five letter words using the identical amplifiers used in the current study. As in this study, Speier et al. (2012) used row and column flashes on a 6×6 grid positioned on meter from the subject. The main differences in this study’s paradigm are the ISI used (Speier et al. used an interval of 125 ms) and electrode placement (Speier et al. used 32 EEG electrodes arranged according to the 10–20 system). More data was collected by the prior Speier et al. study, because of the greater ease of collecting EEG-based data.

2.4 Classification

Analysis was performed offline using MATLAB (version 7.10.0, MathWorks, Inc, Natick, MA). Stepwise linear discriminant analysis (SWLDA) was used to determine the features for classification. Cross-validation was used for training, resulting in one of the trial words being used as the test set with the other two as the training set. The training set signals were then assigned labels based on whether the associated stimulus contained the target character.

For each stimulus, the ECoG data recorded by each electrode over the next 500 ms were appended to create the feature vector, z_t^i for stimulus i for letter t in the sequence. The dimensionality of the feature vector was then 20 times the number of electrodes recording for that subject. SWLDA used a stepwise method to separate the available features into two groups based on whether the feature was significant in classification. At each step, the most significant feature above a threshold in the non-significant group was added to the significant group. Similarly, the least significant feature below a threshold in the significant group was removed from use in classification. The probabilities of adding and removing features were 0.1 and 0.15 respectively. These steps were repeated until the number of significant features reached a threshold of 60 features or until the feature groups reached equilibrium. These significant features were then stored in a weight vector, w . (Krusienski et al. 2006)

During testing, the dot product between the feature vector for each stimulus and the feature weight vector was taken to determine a score for that stimulus:

$$y_t^i = w \cdot z_t^i$$

The static method of classification was then performed by finding the character that had the highest total score for all of the stimuli it was associated with:

$$\arg \max_{x_t} \sum_{i: x_t \in A_t^i} y_t^i$$

where A_t^i is the set of characters illuminated for the i th flash for character t in the sequence.

The number of stimuli is predetermined on a per subject basis so that a decision will be made after a set number of flashes. We simulated this by varying the number of sets of flashes from 1 to 10. After the required number of flashes was reached, we made the decision and discarded the remaining data.

Discarding data in this way overemphasizes earlier trials and underutilizes our data in earlier decisions. We overcame this by taking advantage of the fact that each set of flashes was independent, so the order did not matter. For each letter, we created 1000 random permutations of the sets of stimuli and analyzed each independently, effectively bootstrapping the data. This gave us extra examples of the earlier decisions and used each stimulus equally.

2.5 Spectral Features

We computed spectral features of the ECoG signal following stimulus onset and adding them to the feature vector. The spectrogram was computed using the Chronux toolbox (Bokil et al. 2010) with a moving window of 100 ms and a step size of 50 ms. For each stimulus, the log power of the spectrogram values over the following 500 ms were used as features for classification. To reduce the total number of features, the values in the low gamma (30–70 Hz) and high gamma (70–200 Hz) were averaged.

The resulting features for each channel were then appended to the temporal features to create a new feature vector, $z_t^{'i}$. SWLDA was then retrained on these new features to obtain a new weight vector that contains weights for each of the significant temporal and spectral features.

This dimensionality of the feature and weight vectors is the sum of the numbers of temporal and spectral features. As before, classification was performed by taking the dot product of this weight vector with the new feature vectors obtained for each stimulus to obtain a scalar value for the score.

$$y_t^{'i} = w^{'i} \cdot z_t^{'i}$$

2.6 Natural Language Processing

As a final step, language domain knowledge was integrated into the system to test the additional speedup from using an NLP algorithm as described in (Speier et al. 2012). As in the previous analysis cross-validation was used to obtain a training set for SWLDA. The means and standard deviations were then found for the scores for target and non-target stimuli. Assuming a normal distribution, the probability density function (PDF) for the likelihood probability were computed,

$$f(y_t^i|x_t) = \begin{cases} \frac{1}{\sqrt{2\pi\sigma_a^2}} e^{-\frac{1}{2\sigma_a^2}(y_t^i-\mu_a)^2} & \text{if } x_t \in A_t^i \\ \frac{1}{\sqrt{2\pi\sigma_n^2}} e^{-\frac{1}{2\sigma_n^2}(y_t^i-\mu_n)^2} & \text{if } x_t \notin A_t^i \end{cases}$$

where μ_a , σ_a^2 , μ_n , and σ_n^2 are the means and variances of the distributions for the attended and non-attended scores, respectively.

A Naive Bayes classifier was then used to determine the conditional probability of a target character given a set of flash scores and the history of previous decisions.

$$P(x_t|y_t, x_{t-1}, \dots, x_0) = \frac{1}{Z} P(x_t|x_{t-1}) \prod_i f(y_t^i|x_t)$$

where $P(x_t|x_{t-1})$ is the character bigram probability computed from the Brown corpus (Francis and Kucera, 1979), $f(y_t^i|x_t)$ are the PDFs for the likelihood probabilities and Z is a normalizing constant. Once the probability for a character reaches a threshold, that character is chosen and the system moves on to the next character in the sequence. The threshold probability was varied between 0 and 1 in increments of 0.01 and the value that maximized the bit rate was chosen for each subject.

2.7 Evaluation

When evaluating a BCI system, there is a tradeoff between the accuracy of the system and the speed at which it makes decisions. When more time is allotted for choosing a character, the more data that can be acquired and the more accurate that decision will be. However, increasing the time between decisions decreases the speed of the system. Both of these values need to be taken into account when evaluating the system.

Bit rate is a metric that incorporates both speed and accuracy to describe the rate of information transmitted by the system. It is based on information theory principles described in Pierce (1980) and first implemented in BCI application by McFarland et al. (2003). The number of bits of information per selection is found by considering the number of possible selections and penalizing based on the probability of an error.

$$B = \log(N) + P \log(P) + (1-P) \log\left(\frac{1-P}{N-1}\right)$$

Here, N is the number of possible selections (36 in this study) and P is the accuracy. The information rate is then found by dividing this by the average time required to make a selection, taking the 3.5 second pause between characters into account.

3. Results

3.1 Evoked Response

In general, an evoked response was seen in electrodes starting at 100 ms after stimulus presentation (Figure 2). This response was usually characterized by an initial negative response at 100 ms followed by a positive inflection at approximately 200 ms. This response

is most pronounced in the electrodes near the occipital pole in the electrode grid in subject 1 (Figure 2a–b). It can also be seen in the electrodes in the occipital basal strip in subject 2 (Figure 2d). The electrodes in subject 2's temporal basal strip showed a small negative inflection in response to stimuli (Figure 2e).

3.2 Spectral Analysis

Both subjects showed similar frequency responses to stimuli. Electrodes close to the occipital pole generally exhibited an increase in power about 100 ms after stimulus onset followed by a decrease in power after about 200 ms (Figure 3). The first subject initially saw an increase in beta band power followed by an increase in low and high gamma power with a peak around 130 Hz (Figure 3a). Subject 2 saw a peak in the alpha band after about 150 ms along with a general increase in low and high gamma power. In general, the first subject had a larger frequency response as his spectrogram contained a maximum of 8.6 dB compared to 5.8 dB for subject 2.

3.3 BCI Performance

In our offline analysis, we found that the first subject was able to achieve an accuracy of almost 95% after two sets of flashes and over 98% after three sets using the standard classification method (Figure 4a). His maximum bit rate of 41.02 was achieved after one set of flashes when he had a selection rate of 11.32 and an accuracy of 82.77% (Figure 5a). The accuracy of the second subject was lower, reaching 73.33% after all 10 sets of flashes (Figure 4b). After two sets of flashes, the subject achieved an accuracy of 59.03% and a selection rate of 8.72 characters per minute for a maximum bit rate of 18.26 (Figure 5b). (Table 1)

Using spectral features alone for classification, the two subjects achieved maximum bit rates of 33.55 and 6.04 respectively, which were both lower than the values computed from temporal features alone. When the spectral features were combined with the temporal features for classification, the first subject's accuracy started slightly lower but rose faster, reaching 95.41% after two sets of flashes. The resulting maximum bit rate was 41.97, which was lower because it occurred after one set of flashes. The second subject's maximum bit rate increased slightly as she achieved a selection rate of 8.73 and an accuracy of 60.84 for a bit rate of 19.16. Overall, the average maximum bit rate rose slightly from 29.64 to 29.75.

After integrating language information in the temporal classifier, the first subject achieved a maximum bit rate of 48.81 with a selection rate of 10.53 and an accuracy of 95.09%. When spectral features were added to this classification, the selection rate became 10.41 and the accuracy rose to 96.31 for a maximum bit rate of 49.47 (Table 1). The second subject's maximum bit rate rose to 24.24 with a selection rate of 11.17 and 75.81% accuracy. Adding spectral features increased the bit rate to 27.05 with a selection rate of 8.64 and accuracy of 64.87 (Table 1).

Overall, the bit rate increased significantly with the inclusion of language information and spectral features, as the average increased from 28.56 to 38.26 ($p=0.006$ using a paired t-test with 1 degree of freedom). The average accuracy also increased significantly ($p=0.03$) while the selection rate had a non-significant decrease ($p=.22$).

3.4 Spatial Analysis

In order to find the cortical locations most useful in classification, spatial analysis was performed on the ECoG electrodes. For each patient, each electrode was used individually to classify each of the 150 sets of flashes, so that every electrode had an associated score based on its single flash classification accuracy. The electrodes were then plotted on the cortical

surface and convolved with a Gaussian kernel to obtain a spatial classification accuracy map.

Individual electrode classification accuracies were tested for significance using a Pearson's chi-squared test with one degree of freedom, an alpha level of .05, Yates's correction for continuity, and Šidák correction for multiple comparisons (Figure 6). The distribution of the total weight assigned by SWLDA across electrodes was also evaluated.

The channels for the first subject yielded accuracies that ranged from 0 to 59% with 16 exhibiting significant classification accuracies (Figure 6a). Two of the electrodes on the posterior basal occipital strip, four of the six midline electrodes, and ten of the electrodes in the occipital grid were found to be significant, focused mainly around the occipital pole.

The channels for the second subject yielded accuracies that ranged from 0 to 27% with five exhibiting significant classification accuracies (Figure 6b). In general, the temporal grid and the suprasylvian and middle posterior temporal basal strips were not useful as none of the electrodes had significant accuracy. The posterior temporal basal strip had one significant electrode with a maximum of 15% accuracy. The occipital basal strip had the best classification accuracy as it contained four significant electrodes, including the best performing electrode with an accuracy of 27%.

3.5 EEG comparison

To make the comparison fair, we reanalyzed the EEG dataset used by Speier et al. (2012) to find the results for the standard analysis as well as the NLP algorithm with spectral features (Table 2) using the bootstrapping method described in section 2.4. Overall, the subjects in this study performed better than those in the EEG study. On average, the subjects in this study achieved a selection rate of 10.02 selections/minute with an accuracy of 70.90% before integrating language information, resulting in a bit rate of 29.64. This was higher than the EEG averages bit rate of 21.69. Using the NLP algorithm, the average selection was to 9.52 selections/minute and the accuracy rose to 86.06%, resulting in an average bit rate of 38.26, which was higher than that for the EEG study (32.06).

The average improvement seen in this study is primarily due to the performance of the first subject. Using the standard analysis, the first subject had a significantly higher bit rate ($p=0.004$ using Wilcoxon rank-sum test) as the selection rate and accuracy were both better than the averages in the EEG data set. Using the NLP algorithm, the first subject's bit rate was still higher than the average for the data set, but the difference was only marginally significant ($p=0.017$). In both cases, the first subject had a higher bit rate than any of the subjects in the EEG data set, although one was close when using the NLP algorithm.

The second subject's bit rate was below the average for the EEG data set, but the difference was not statistically significant ($p=0.38$) and she performed better than three of the subjects from the EEG study. Her bit rate was still below the average for the EEG average using the NLP algorithm, but was still higher than the three subjects from the data set. Potential sources for variability and inferior performance were explored further (see Spatial Analysis below).

4. Discussion

4.1 System performance

ECoG-based P300 spellers can improve system performance relative to EEG-based systems, both with respect to accuracy and bit rate. This improved performance however is sensitive to electrode localization, as is evident in comparing the performance of the two subjects who

had electrodes in different areas. Even without any modifications to the classification algorithm, the first subject achieved a higher accuracy with fewer stimuli than any of the subjects in the EEG data set or noted otherwise in the literature. The improved performance (bit rate) was despite using a higher ISI (150 ms) than the EEG study (125 ms) which meant that the selection rates and bit rates in this study would otherwise be lower than those for a similar subject in the EEG study. It is well known from the literature that stimulus timing parameters, particularly ISI, can significantly impact classification accuracy (Sellers et al., 2006; Lu et al., 2012). Optimizing system parameters for this system could lead to better improvements (see limitations and future directions).

The sensitivity to electrode localization is evident in the results of the second patient, as she performed worse than the average for the EEG data set. The spatial analyses for these two patients show one possible explanation for the difference between the two patients. The single flash accuracies of electrodes generally increased the closer the electrodes were to the occipital pole. While the first patient has electrodes through the occipital region, the second patient has only sparse coverage, consisting mainly of strips in the basal region. The difficulties shown by the second patient suggest that performance in an ECoG based BCI is sensitive to electrode placement. While this subject had more electrodes available and wider coverage than the first subject, her performance was significantly worse in both accuracy and selection rate. While we cannot test the locations outside of the ECoG coverage for this subject, the electrodes within the overlapping regions for the two patients had similar accuracies. This suggests that there could have been a strong ERP in the occipital region of the second subject that was not detected due to the electrode placement, accounting for some of the difference in performance. This is consistent with previous work which showed a drastic drop in performance when occipital electrodes were not used in analysis (Brunner et al., 2011).

The timing and localization of the signals detected in our analyses suggest that this system is based on visually evoked potentials (VEP). This is significant since VEP is highly dependent upon eye gaze, which severe locked-in patients may not be able to control. It has been shown that performance drops drastically in EEG-based systems when the eye gaze is constrained (Brunner et al., 2010). The effect of eye gaze in an ECoG based system remains to be studied (see Future Work).

4.2 Spectral Features

Using spectral features alone, the classifier bit rates were lower than when using temporal features, but they were close on average to the EEG bit rate. Including spectral features with temporal features in the analysis increased the bit rates for both subjects when using the NLP analysis method. Further analysis using a larger sample size is required to definitively evaluate the value of incorporating spectral features in ECoG P300 analysis, but a sufficient sample size was unavailable at this time due to the unique and rare opportunities available to study such subjects.

The EEG dataset bit rate stayed relatively constant (31.97 to 32.06, $p=.30$) with the inclusion of spectral features. This could be because of the lower signal to noise ratio of EEG or because the lower sampling rate used in this dataset was too low to detect high frequency components.

4.3 Natural Language Processing

Integrating language information into the classification resulted in significant increases in bit rate and therefore overall system performance. The magnitude of improvement (22% in the first subject) however was lower than the 40–60% improvements reported in (Speier et al.,

2012). We posit that this is due to a ceiling effect. Because the subject's performance was already at such a high level, language information was not always needed. Since the subject was already achieving perfect accuracy the only possible improvement would be from reducing the time required. This is in contrast to the second subject who in fact experienced a 41% improvement with the use of the NLP algorithm as the bit rate improved from 19.16 to 27.05, consistent with those shown in the previous study.

4.4 Similar work

Brunner and colleagues also tested the P300 speller using ECoG signals (Brunner et al., 2011). Their study consisted of one patient and their analysis focused on a 6-electrode strip over the occipital cortex. Their study reported a substantially higher bit rate than either of the patients in this study. Our first subject achieved similar accuracy to theirs after the same number of stimuli, but our stimulus presentation rate was slower resulting in a lower bit rate. This would suggest that our presentation rate could have been increased without much loss in accuracy, although this was not tested. We leave finding the relationship between presentation rate and accuracy as well as optimizing system parameters in an ECoG system as future work.

Krusienski and Shih performed a P300 speller study on six epilepsy patients with ECoG electrodes implanted in the frontal, temporal, and parietal regions (Krusienski and Shih, 2011a). While five of the six patients were able to perform reasonably well, the average accuracy was shown to be close to that achieved by their EEG study and none of the subjects performed as well as subject 1 in this study or the subject in the Brunner study. This is likely due to the electrode placement as none of the subjects in their study had coverage of the occipital cortex.

Our experiment serves to verify the results of the previous studies showing the viability of using ECoG for the P300 speller as well as expanding on the spatial analysis by showing results in a broad cortical area. We also show additional improvements that can be made on these results using language information and potentially spectral features to achieve even better P300 speller performance.

4.5 Limitations and future directions

While the performance of the first subject suggests that an ECoG based BCI system could yield better performance than current systems, more subjects need to be tested. This is in fact challenging as the placement of occipital grids and strips for epilepsy monitoring (which is the only model available for investigating this phenomenon) is relatively rare. Most such strips and grids are placed over frontal and temporal cortices. Also, showing the difference in performance within subjects would be a better indicator for the improvement from using this modality. In an ideal situation, we would be able to test the EEG system on a subject before the ECoG electrode placement surgery. Unfortunately, this was not possible in the current set of subjects studied.

Since the ECoG grids in our subjects were placed according to their seizure localization, the locations that we could use for our testing were limited. In particular, we were not able to test the parietal lobe, where the P300 signal occurs. We also were not able to test the system using data from the occipital pole of the second patient. Time constraints imposed by clinical parameters also prevented further system parameter optimization, such as stimulus length and ISI. Future studies will test patients with different electrode placements to more completely explore the electrode configuration space.

One of the major drawbacks for the approach described in this paper is the invasive surgery required to implant the electrodes. Even though the many ALS patients may be willing to

undergo invasive surgery in order to obtain a better BCI (Huggins et al., 2011), it would still be preferable to limit the risks involved in surgery. While the added speed and accuracy of this system could make the procedure worthwhile to patients, we still want to minimize the extent of the surgery required. For this reason, a future direction for this work is to explore the use of epidural implants as a compromise between risk and benefit.

Finally, the subjects used in this study were not from the target patient population of “locked-in” patients. Since our subjects are not suffering from the same deficiencies, these results might not translate into identical improvement in the target population. For example, the spatial analysis in this study showed that the occipital region yielded the best results. Some severe “locked-in” patients are not able to move their eyes, however, so a system depending on occipital signals might not be appropriate. It remains to be seen if this system leads to actual improvements within our target population.

4.6 Conclusion

This study demonstrates that ECoG could potentially increase the accuracy and bit rate of a BCI system, but that the system is sensitive to the placement of the electrodes. Integrating language information significantly improved the system and integrating spectral features showed an increase in bit rate that suggests that they could be useful as a supplement to traditional temporal features. Testing additional subjects, including those from our target patient population, could help verify that this improvement is enough to justify the required surgery and ultimately provide a better option for ALS patients.

Acknowledgments

We gratefully acknowledge the assistance of Kirk Shattuck in facilitating signal splitting for the purposes of these experiments.

This work was supported by the NLM Training Grand T15-LM007356 (WS), the National Institute of Biomedical Imaging and Bioengineering Award Number K23EB014326 (NP), the UCLA Scholars in Translational Medicine Program (NP), and the UCLA Department of Neurosurgery Visionary Ball Fund.

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Highlights

- Electrocortigraphy-based P300 spellers can significantly outperform traditional EEG-based systems, with bit rates as high as 40.
- Even further improvements in electrocortigraphic P300 speller system performance can be realized with integration of natural language processing into the classifier model with bit rates approaching 50.
- Electrocortigraphic P300 speller performance significantly depends on electrode localization, with far superior performance seen when employing electrodes over the occipital pole.

Figure 1. Images of implanted electrodes. (a) Photograph of the craniotomy and implanted electrodes for subject 1. (b) Intensity-inverted anteroposterior x-ray of the subject 1 with implanted electrodes. (c) Photograph of the craniotomy and implanted electrodes for subject 2. (d) Intensity-inverted lateral x-ray of subject 2 with implanted electrodes.

Figure 2. Average signal amplitude (in μV) over time (in ms) for response to attended (solid) and non-attended (dashed) stimulus for selected electrodes. For subject 1 (a), signals for the electrodes in the occipital grid are plotted (b). For subject 2 (c), signals for electrodes in the posterior temporal basal (d) and occipital basal (e) strips are plotted. Note that differentiation occurs between attended and non-attended signals in electrodes close to the occipital pole.

Figure 3. Log ratio of spectral response between target and non-target stimuli after onset along with average temporal response for a single electrode from each subject. The electrode from the occipital pole was used from subject 1 (a) and the middle electrode in the occipital basal strip from subject 2 (b) along with the average temporal response for attended (solid) and non-attended (dashed) stimuli.

Figure 4. Subject accuracies. The average accuracies for each subject are plotted using the standard (broken curve) and NLP (full curve) methods versus the average number of sets of flashes required to make a decision.

Figure 5. Subject bit rates. The average bit rates for each subject are plotted using the standard (broken curve) and NLP (full curve) methods versus the average number of sets of flashes required to make a decision.

Figure 6. Event-related potential localization. The white dots show the locations of the electrodes and the cortical surface is color-coded based on the single-flash accuracy of the nearby electrodes. Electrodes that are statistically significant are highlighted in blue.

Table 1

Results for the standard classification as well as the NLP method with spectral features optimized for bit rate.

Subject	SR (selections/min)		Accuracy (%)		Bit Rate (bits/min)	
	Standard	NLP + Spec	Standard	NLP + Spec	Standard	NLP + Spec
1	11.32	10.41	82.77	96.31	41.02	49.47
2	8.73	8.64	59.03	75.81	18.26	27.05
AVG	10.02	9.52	70.9	86.06	29.64	38.26

Table 2

Results for the standard classification as well as the NLP method with spectral features optimized for bit rate for the EEG data set included for comparison.

Subject	SR (selections/min)		Accuracy (%)		Bit Rate (bits/min)	
	Standard	NLP + Spec	Standard	NLP + Spec	Standard	NLP + Spec
1	9.23	10.51	86.22	94.4	35.86	48.05
2	7.5	8.78	73.54	87.46	22.34	34.95
3	9.23	9.68	79.17	93.84	31.05	43.76
4	5.45	7.54	74.76	81.56	16.69	26.67
5	5.45	6.79	54.83	66.05	10.14	16.99
6	4.29	6.86	72.58	76.84	12.5	21.95
AVG	6.86	8.36	73.52	83.36	21.43	32.06