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Improving ECoG-based P300 speller accuracy

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Abstract

Brain-Computer Interfaces (BCIs) are expected to become a game-changing modality for the communication and control of both devices and virtual environments in humans whose direct neuromotor response needs to be augmented, bypassed, or replaced. Recent developments in the area of BCI research suggest that subdural electrocorticography (ECoG)-based BCIs might be more efficient than scalp electroencephalography (EEG)-based ones. In this study we compared the performance of an EEG-based P300 speller BCI (which allows typing without utilizing muscular activity) to an ECoG-based one. Three different approaches (i-iii) were used to select the best electrode sites from acquired ECoG signals. We found that the ECoG-based P300 speller performance accuracy varied widely between the different approaches. Approach iii, based on the choice of the longest duration of significant difference between TARGET and NON-TARGET stimuli, provided the most accurate ECoG-based results. Those results were comparable to and even surpassed the EEG-based results. However, the invasive nature of ECoG-based electrode selection has its own disadvantages. Therefore, as a future perspective, we propose to explore the potential contribution of non-invasive methods (for example, magnetoencephalography – MEG) to augment the subdural/depth electrode placement process.

1 Introduction

Brain-Computer Interfaces (BCIs) are powerful tools for enabling communication between people and the surrounding world using direct brain activity recorded non-invasively from the scalp (EEG), invasively from the brain surface (ECoG), or from deep within the brain itself using depth electrodes (Shih & Krusienski, 2012). The need for BCIs is immense as it can benefit a number of clinical populations, such as people with stroke, locked-in syndrome, amyotrophic lateral sclerosis (ALS), and other severe disorders involving deterioration or damage of muscular system (Silvoni, et al., 2013) (Birbaumer, Gallegos-Ayala, Wildgruber, Silvoni, & Soekadar, 2014). The "P300 speller" is currently the most popular BCI system enabling communication by spelling words or phrases with direct brain-controlled selection from menus presented on a computer screen (Farwell & Donchin, 1988). People achieve up to 91% accuracy with a speed of 2-3 characters per minute using a scalp EEG-based P300 speller (Guger, et al., 2009). However, some questions still remain: (1) Are ECoG-based BCIs superior to the EEG-based ones? and (2) How can the performance of ECoG-based BCIs be further improved? Recent, though limited, reports (Shih & Krusienski, 2012) suggest that invasive ECoG-based BCIs can be faster and more accurate than non-invasive EEG-based BCIs. Approaches to

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improve the accuracy of ECoG-based P300 speller have been proposed (Speier, Fried, & Pouratian, 2013), however they still need further development. Therefore, in this study we sought (1) to compare ECoG- and EEG- based BCI performance; and (2) to maximize performance of the ECoG-based P300 speller by applying different approaches to the selection of electrodes chosen for ECoG signal detection.

2 Methods

One female and 3 male patients (mean age 23 +/-10.6) diagnosed with intractable epilepsy and undergoing evaluation for resective epilepsy surgery were recruited. Two patients (#1 and #2) underwent both EEG- and ECoG-based recordings with P300 speller; while two other patients (#3 and #4) underwent only an ECoG-based P300 speller session. Participants received both character- and face-based stimuli in the testing sessions.

2.1 Training

Each participant was presented with three 5 character words to train the linear classifier to distinguish the P300 response. The row/column speller that flashes an entire column or row of characters was utilized. Flashing rows and columns were each presented 15 times (15x15) and an individual classifier was calculated before the "free spelling" experiment began. All active electrodes (8 total) were used for free spelling based on EEG recordings, whereas the 8 "best" were chosen for each subject from all possible ECoG electrodes. The criteria for selecting the 8 "best" in each approach are detailed below.

2.2 Free spelling

The free spelling began with presenting flashing rows and columns 15 times each. The number of flashes was gradually decreased while the desired level of difficulty was obtained. The decrease was done in the following increments: 15, 8, 4, 2, and 1. A 5 character word was used for each level of difficulty.

2.3 EEG-based recording

The EEG data were acquired from 8 electrodes (Fz, Cz, P3, Pz, P4, PO7, POz, PO8) using a g.USBamp (24 Bit biosignal amplification unit, g.tec medical engineering GmbH, Austria) at a sampling frequency of 256 Hz. The ground electrode was located on the forehead while the reference was mounted on the right earlobe (Guger, et al., 2009).

2.4 ECoG-based recording

The total number of subdurally placed electrodes available to be used from synchronized g.USBamp devices varied for each of the individuals. The data was analyzed with g.BSanalyze Matlab-based program (g.tec Medical Engineering GmbH, Austria) and additional Matlab scripts created by engineers from g.tec medical engineering GmbH. These approaches were used to screen all available ECoG electrodes and identify 8 most informative ones for free spelling (number "8" is chosen to have a fair comparison with scalp EEG P300 speller performance; the same number of electrodes and the same algorithms are used): (i) choosing the signal with the highest amplitude; (ii) choosing the signal with the lowest correlation between standard and deviant responses; (iii) choosing channels based on the longest duration of significant difference ($p<0.05$) between TARGET and

NON-TARGET trials. The ECoG electrode locations for P300 speller varied between study participants. The main regions of overlap included frontal and central cortex (patients #1-3). In addition, patient's #3 electrodes were located in occipital cortex.

3 Results and Discussion

3.1 EEG-based recording

Accuracy in EEG-based recordings varied with different classifiers (ranging between 30% and 100%). It reached a maximum of 100% in patient #2 when three classifiers were combined for 15x15 presentation rate. Interestingly, accuracy was higher with faces of popular people (reaching 90% in most conditions) rather than simple flashing letters.

3.2 ECoG-based recording

Accuracy in ECoG-based recordings was significantly lower (ranging between 0% and 11%) in patients #1-#3 with flashing rows and columns each presented 15 times (15x15) than EEG-based recordings in patients #1 and #2 using approaches i and ii. Performance may be affected by the location on the brain surface of the grid coverage and a failure to identify the "best" channels. We aimed to investigate if the low accuracy results can be attributed to identification failure of the "best" channels. Therefore, approach (iii) was developed – see section New Analysis Approach.

3.3 New analysis approach

In order to improve accuracy of ECoG-based P300 speller performance, a new P300 analysis approach to identify the best 8 ECoG channels was developed and tested in patient #4. P300 responses were analyzed as follows: 1) A butterworth filter 4^{th} order 0.1 Hz to 30Hz was applied and data was triggered into TARGET and NON-TARGET trials; 2) Artifacts were identified and removed; 3) A Mann-Whitney U-test was used to test if TARGET and NON-TARGET samples originate from the same distribution and led to a p-value for each sample and channel. The channels were selected according to the longest period of significant difference ($p<0.05$) between TARGET and NON-TARGET trials. The results with approach iii are presented in Figure 1.

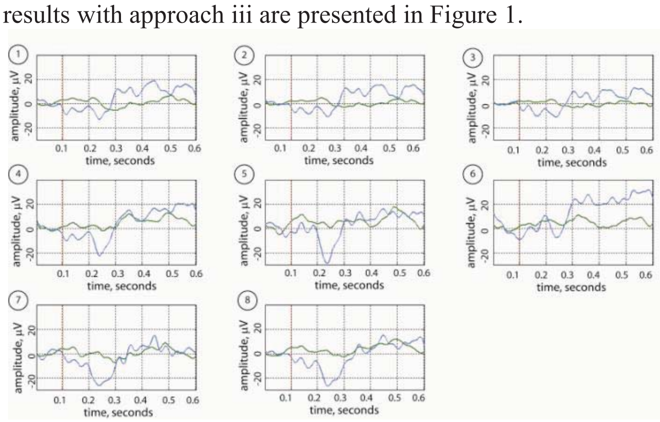

Figure 1. Best eight ECoG P300 responses using approach iii in subject #4 Average signal amplitude over time for response to TARGET (blue) and NON-TARGET (green) stimuli.

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Importantly, with approach (iii) for the selection of electrodes, the accuracy of the ECoG-based P300 speller surpassed results from approaches i-ii, as well as scalp EEG-based P300-speller by providing with accuracy ranging from 85% to 100% (again, for a session with flashing rows and columns each presented 15 times).

4 Conclusions

Intracranial grid placement may provide users with unique opportunity to control real and virtual worlds with high speed and accuracy. ECoG-based P300 speller can provide comparable results to the EEG-based one in terms of accuracy. In fact, it can surpass EEG-based P300 speller accuracy. Moreover, this accuracy can be further improved. Indeed, the identification of the "best" locations of ECoG electrodes plays very important role in ensuring high accuracy of P300 speller performance. Our proposed signal processing algorithm based on the duration of the significant difference between TARGET and NON-TARGET responses may be of high value to achieve this goal. It is important note, that this approach is based on information from invasively implanted ECoG electrodes. Because the location of the BCI implantation site may play a critical role in performance, we believe that future approaches should explore non-invasive procedures, such as magnetoencephalography (MEG), to enhance ECoG electrode placement. We suggest that one of the optimal ways to achieve maximal P300 speller performance is: (1) use intracranially/subdurally implanted electrodes; (2) navigate electrode implantation with non-invasive methods; and (3) utilize quantitative approaches/algorithms based on available ECoG information for the choice of the best electrodes.

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