# Non-Invasive Versus Invasive Brain-Computer Interfaces

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***Abstract.*** Surgically-implanted, intracranial Brain-Computer Interfaces (BCIs) are expected in the future to become a radical, game-changing modality for the control of virtual environments by humans whose direct neuromotor response needs to be augmented or replaced altogether. Recent developments in the signal processing of electrocorticographic (ECoG) signals have suggested that surgically-based intrcranial ECoG can form a more efficient BCI than non-surgical scalp EEG. In this preliminary study, we aimed to compare the effectiveness of intracranial versus scalp-based BCIs. We conclude that although surgical BCIs can be effective, specific approaches must be developed to identify and extract the data of interest from ECoG recordings.

*Keywords:* Brain-computer interfaces (BCIs), P300 speller, Electrocorticography (ECoG)

## 1. Introduction

Brain-Computer Interfaces (BCI) are powerful tools for enabling communication between people and the surrounding world using direct brain activity recorded non-invasively from the scalp (electroencephalogram, EEG), invasively from the brain surface (electrocorticogram, ECoG), or from deep within the brain itself using depth electrodes [Shih and Krusienski, 2012]. The non-invasive “P300 speller” paradigm is the most frequently used approach that allows subject to spell words or phrases by direct brain-controlled selection from menus presented on a computer screen [Farwell and Donchin, 1988]. People achieve 91% accuracy with a spelling speed of 2-3 characters per minute [Guger et al., 2009]. However, some recent published reports [Shih and Krusienski, 2012] have suggested that invasive ECoG-based BCIs can be faster and more accurate than non-invasive EEG-based BCIs. Yet no studies to date have directly compared non-invasive versus invasive “P300 spellers” in the same individuals. In this study, we performed paired comparisons of the “P300 speller” BCI in both invasive and non-invasive settings in the same subjects. We hypothesized that invasive “P300 speller” will be more efficient than its non-invasive version.

## 2. Methods

Three patients (3 males; age 25±14.2) diagnosed with intractable epilepsy and undergoing evaluation for resective epilepsy surgery were recruited. They underwent scalp and intracranial testing with P300 speller. Two different types of P300 speller were used: character-based and face-based.

Training: Each participant was initially presented with 3 words (5 characters each). This was done in order to train the linear classifier to distinguish the P300 response. The training included flashing rows and columns – 15 times each. Individual classifier was calculated based on the acquired information. Afterwards a “free spelling” experiment began. All 8 electrodes were used for free speller based on scalp recordings, whereas 8 best electrodes were chosen based on certain characteristics (see Data Evaluation/Analysis section) for free spelling experiment from subdural electrodes. 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 gradual decrease included the following number of flashes: 15, 8, 4, 2 and 1. For each level of difficulty, the 5 character word was used. 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; the reference was mounted on the right earlobe [Guger et al., 2009].

The ECoG data were acquired using g.USBamp devices (24 bit biosignal amplification unit, g.tec Medical Engineering GmbH, Austria) at a sampling frequency of 1200 Hz. Subdurally placed reference and ground electrodes were used. The number of electrodes 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. Three main approaches were used to choose best 8 subdural electrodes for free spelling: (1) choosing the signal with the highest amplitude; (2) choosing the signal with the lowest correlation between standard and deviant responses; and (3) significance test based sample-wise computed coefficient of determination, testing the null-hypothesis that target and non-target trials have equal mean amplitude.

## 3. Results and Discussion

Accuracy in scalp recordings was reaching 100% for 15x15 presentation rate, 70% for 8x8 presentation rate, 60% for 4x4 presentation rate, 80% for 4x4 presentation rate and 0% for 1x1 presentation rate. Interestingly, using faces (of different popular people in this case) instead of simple flashing letters provided with higher accuracy reaching 90% in most of the conditions.

Differently from what was predicted, intracranial recordings did not provide with high “P300 speller” accuracy. It was significantly lower for all presentation rates when compared with the “P300 speller” accuracy achieved with scalp recordings. The difficulty was observed in choosing the right locations for 8 channels needed to calculate the classifier. Electrode locations based on the proposed algorithm #1 were not always concordant with the locations determined by using algorithm #2.

We hypothesized that the failure of intracranial “P300 speller” to provide with high accuracy results was related to the algorithms #1 and #2 used for the selection of major 8 electrodes for calculating the classifier. Therefore, a new approach was developed, which included the following processing steps: 1) The common average reference over all channels was calculated; 2) The triggers on each channels were extracted; 3) Signal was baseline-corrected by using de-trend function; 4) All artifacts were removed from the recording (all trials with amplitudes > 1000 µV are rejected); 5) Sample-wise correlation between non-target and target responses was calculated; 6) Significance test based on the correlation coefficients was used. This new approach lead to the results different from those obtained with previous analysis methods (Fig. 1).

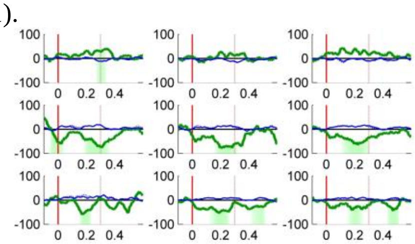

***Figure 1.*** *Example of using approach #3 to process intracranial P300 responses in subject #10. With green is indicated response to targets and in blue – response to non-targets. Y-axis indicates response amplitudes (mkV) and X-axis indicates response latencies (ms). Regions between target and non-target with significant different mean value are highlighted in green.*

## 4. Conclusions

Intracranial grid placement may provide users with unique opportunity to control real and virtual worlds with high speed and accuracy. However, specific signal processing approaches to achieve this accuracy still need to be developed. Our proposed signal processing algorithm may be of high value to achieve this goal. However, this is the first test of the algorithm the validation of the whole procedure is needed before it may be used in real settings.

### Acknowledgements

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