# DETECTION OF MOVEMENT INTENTION ONSET FOR BRAIN-MACHINE INTERFACES

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## INTRODUCTION

"Brain-machine interface" (BMI) broadly describes technologies whereby electrical impulses from a user's brain are used as control signals for one or more output pathways. In many cases, this takes the form of signals from primary motor cortex, which can be generated by the user intending to move relevant muscles (Lacourse et al 1999). The purpose of a BMI system is typically to provide access to either communication devices or prosthetics for individuals with severe paralysis (for example, in cases of high-level spinal cord injury). To date, the majority of BMI systems have used a "synchronous" paradigm, meaning that a user must generate neural signals at a time specified by a cue. However, "asynchronous" systems (wherein the system continually searches for inputs from the user) are likely to be more intuitive, user-friendly, and versatile (Townsend et al. 2004). A major step in developing asynchronous BMIs will be to determine effective methods of detecting the timing of a user's intention (in the case of recordings from primary motor cortex, this is the user's intention to move).

The goals of this study were twofold. The first was to develop an automated analysis program for assessing the accuracy of movement onset time predictions. The second goal was to determine the ideal method of predicting movement onset time in pilot data. These methods included both common techniques within the literature (for example, observing changes in specific bandpowers within the signal [Pfurtscheller & Lopes da Silva 1999]) and more novel ones.

## METHODS

Four subjects took part in the study – two with implanted electrocorticogram (ECoG) electrodes, and two with non-invasive electroencephalogram (EEG) electrodes. All recordings were taken from over the subjects' primary motor cortices. Each subject was, while comfortably seated, asked to perform a variety of motor tasks with the arm contralateral to the recording site. The specific tasks varied from subject to subject, but typically included both simple tasks (ie. elbow flexion, wrist flexion) and complex tasks (ie. handwriting, playing simulated tennis on a Nintendo Wii console). In most cases, movements were self-paced, and were performed 25-30 times. While the movements were being performed, neural data was being collected at a sampling frequency of 200 Hz. Electromyogram (EMG) data was simultaneously being collected from relevant muscles.

Data analysis was conducted offline, using custom Matlab scripts that allowed for analysis to occur in an automated fashion. Three consecutive steps were applied. In the first step, the neural data was preprocessed. The original monopolar channels were applied, as were bipolar (differential) channels, and principal components (obtained from principal component analysis of the original monopolar channels). In the second step, these preprocessed signals were used to derive "criterion" signals. A sliding time window was applied to the preprocessed signal, and within that time window, one of several functions was applied to obtain a single value. That value was then used as a single data point in the time-variant criterion signal. The time window was moved one data point forward, and the next point in the criterion signal was obtained in an identical fashion. The functions used to generate criterion signal points were as follows: bandpower (at the following frequency ranges: 1-5, 8-12, 12-20, 20-30, 36-44, and 90-99 Hz), bandpower integral (the sum of all frequency component amplitudes), phase (at the same frequencies as were used for bandpower), variance, sum of differences, fractal dimension, and spectral entropy. In the final step, the discriminative ability of the criterion signal was determined using receiver operating characteristic (ROC) analysis. A set threshold was applied to the EMG signals, to determine whether the subject was 'active' or 'inactive' at any time point. A range of thresholds was similarly applied to the criterion signals, with the intention of scanning the entire range of criterion signal values, to provide a binary prediction of whether the subject was 'active' or 'inactive' at each time point. For each threshold, the true positive rate and false positive rate was determined by considering the agreement between the thresholded EMG and the predictions. Based on these values, the discriminative ability of the criterion signal was determined as the area under the ROC curve (AUC) (made by plotting all of the true positive rates and false positive rates on a Cartesian axis). An AUC value of 0.5 indicated random chance, while a value of 1 indicated perfect predictive ability. The analysis was repeated using a range of values for several parameters. The manipulated parameters are: length of time window applied to generate each criterion signal point, relative time window within which a prediction can be considered to 'match' with a threshold EMG point, which function is applied to generate the criterion function, which type of preprocessing is used, and which channel or principal component is used.

In addition, "change-point analysis" was applied, as described in Moskvina & Zhigljavsky (2003). While this analysis was largely similar to that conducted within the regular analysis described above, methodological issues prevented the method from being directly implemented within the automated framework. A separate change-point analysis program was run on the preprocessed data, which produced a time-variant signal as an output. This signal was then used as a criterion signal to continue the later analysis.

## RESULTS

Results of the ROC analysis are presented in Figure 1. Specifically, this graph represents the maximum AUC value obtained by applying a given analysis function to a given trial of movement.

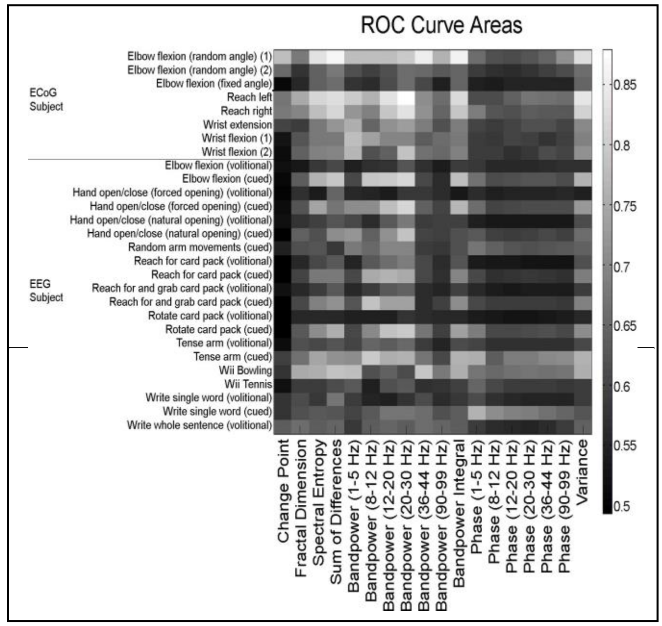


Figure 1: Summary of the best AUC values obtained for a given pairing of trial and analysis type. Lighter shades indicate more accurate predictions, whereas darker shades indicate poorer predictions. An AUC value of 0.5 indicates random chance, while an AUC value of 1 indicates perfect prediction.

Figure 2 presents the most accurate predictions generated by this system.

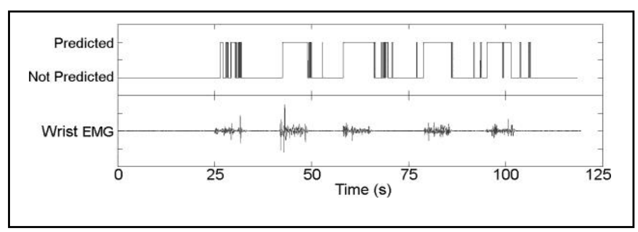


Figure 2: Sample of the most accurate predictions generated (ROC curve area = 0.863). These results are from an elbow flexion trial with Subject 2 (ECoG), and are based on increases in the sum of differences.

Tables 1 and 2 show the percentage of parameter value combinations which generate predictions with AUC ≥ 0.7. If a particular parameter value is ideal, it should have a greater percentage of trials generating these "successful" predictions.

Table 1: Summary of the relative frequencies with which specific parameters gave rise to successful movement onset predictions in the ECoG subjects.

| | | Subject 1 | Subject 2 |
|---|---|---|---|
| | Percent successful | 1.5% | 3.2% |
| Window length | 0.25 s | 3.5% | 26.8% |
| | 0.5 s | 31.5% | 33.8% |
| | 1 s | 65.0% | 39.4% |
| Acceptable window | 0.5 s pre-EMG | 5.2% | 21.1% |
| | 0.25 s pre- or 0.25 s post-EMG | 34.5% | 31.7% |
| | 0.5s post-EMG | 60.3% | 47.2% |
| Preprocessing | Monopolar | 5.3% | 28.5% |
| | Differential | 64.9% | 46.5% |
| | PCA | 29.8% | 25.0% |

Table 2: Summary of the relative frequencies with which specific parameters gave rise to successful movement onset predictions in the EEG subjects.

| | | Subject 3 | Subject 4 |
|---|---|---|---|
| | Percent successful | 7.8% | 0.6% |
| Window length | 0.25 s | 22.0% | 8.7% |
| | 0.5 s | 33.6% | 33.5% |
| | 1 s | 44.4% | 57.8% |
| Acceptable window | 0.5 s pre-EMG | 58.3% | 38.5% |
| | 0.25 s pre- or 0.25 s post-EMG | 39.3% | 27.5% |
| | 0.5s post-EMG | 2.4% | 24.0% |
| Preprocessing | Monopolar | 31.9% | 11.3% |
| | Differential | 48.2% | 38.4% |
| | PCA | 20.0% | 50.4% |

In general, it is noted that most criterion functions (excluding change-point analysis, phase, and the 90-99 Hz bandpower) were able to generate accurate predictions in at least some cases. In general, ECoG cases were able to generate more accurate predictions than EEG cases. However, other than this, no clear pattern was apparent in the effects of other parameters on the eventual accuracy of predictions.

## DISCUSSION

It is suggested, based on the present results, that neural signals from primary motor cortex, as measured through EEG and ECoG, contained sufficient information for accurate predictions to be made about the timing of many different types of movements. Fractal dimension, spectral entropy, sum of differences, most bandpowers up to 40 Hz, the bandpower integral, and variance were all suggested as appropriate methods for deriving this information. However, it was also shown that the accuracy of these predictions was highly dependent upon a number of different parameters, in ways that were not always consistent. Parameter sets that provided ideal results for one subject and movement type may not have provided similar results for another movement or another subject. It is therefore suggested that a wide range of parameter combinations would need to be tested for each case if the techniques developed herein are to be successfully applied to an asynchronous BMI system.

## REFERENCES

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