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Neural Correlates of Graded Movement for Brain-Computer Interfaces

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Introduction

Brain-computer interfaces (BCIs) are designed to collect, process, and translate brain signals into commands for an external device (Fig. 1). This technology offers a new communication pathway that circumvents the peripheral nervous system. Accurate decoding of user intent has tremendous potential to improve rehabilitation efforts or assist in activities of daily living.

Today, BCIs are still primarily limited to research settings due to operational challenges[1], specifically the need to generate and discriminate between brain signals associated with distinct mental tasks to control an external device. If we can leverage the known suppression of cortical sensorimotor activity in the mu and beta bands of the electroencephalogram (EEG) (8-30 Hz), we may be able to overcome such challenges in BCI development.

Objective

To model *graded* event-related potentials (GERPs) from the EEG, i.e., signals that reflect the level of effort associated with a movement task.

Predicting gradations in motor effort associated with a single isometric force production task from the EEG would multiply the number of available command signals.

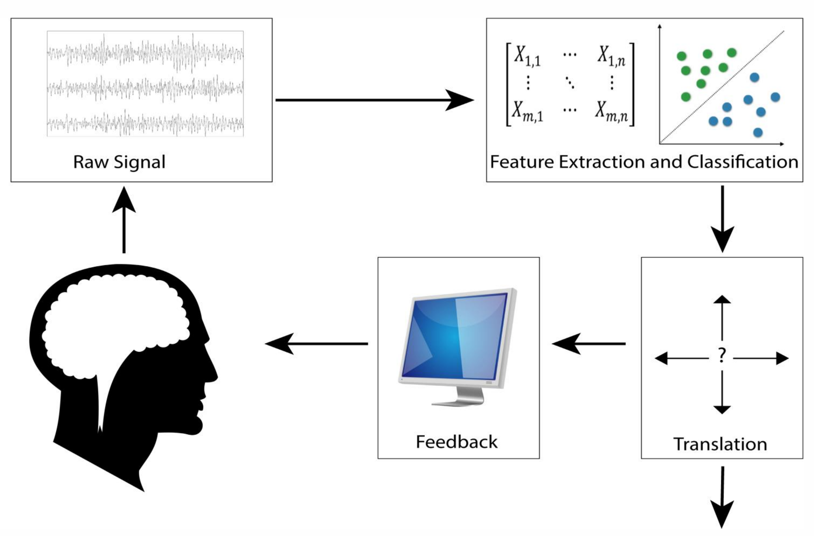

Figure 1. Schematic of a typical brain-computer interface. The three main parts are (1) collection of the raw EEG; (2) signal conditioning, feature extraction and classification; and (3) mapping of the predicted intent class into one of many actions. Natural or artificial sensory feedback closes the loop.

Methods

All procedures were performed with prior IRB approval and informed consent. 14 healthy adult subjects (9 male, 5 female) performed a repetitive task in which they were required to squeeze a hand dynamometer (Vernier, Oregon) in response to a visual cue to reach a target force. The EEG, electromyogram (EMG), and handgrip force were simultaneously measured using a biosignal amplifier (g.HIAmp, g.tec, Austria). Active EEG electrodes were placed at 18 locations on the scalp (Fig. 2). The visual display alternated between different cue states a fixed number of times (Fig. 3A).

Feedback is given to participants based on their applied force and the goal is to squeeze with enough force for the dynamic blue circle to reach the concentric black annulus, which would occur when the exact target force is exerted.

Target forces are set to a percentage of each subject's maximum voluntary contraction force (MVC) on each hand. Four such targets/classes were used here: **20%**, **35%**, **50%**, and **65%** of MVC (Fig. 3C). The rest state target, i.e., **0%** MVC, was included as an additional class.

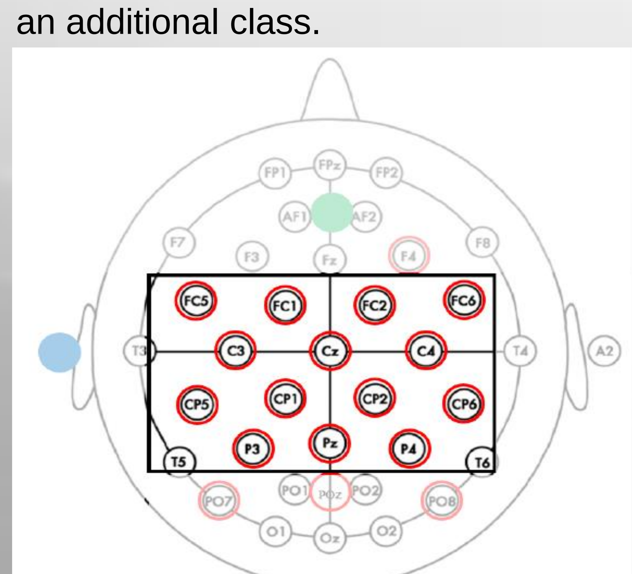

Figure 2. EEG scalp montage. Eighteen electrode potentials (earlobe reference) were recorded with three (PO7, POz, PO8) used to verify signal quality and one (F4) to detect ocular artifacts. The rest, located above motor and sensory cortices, were used in the GERP analysis.

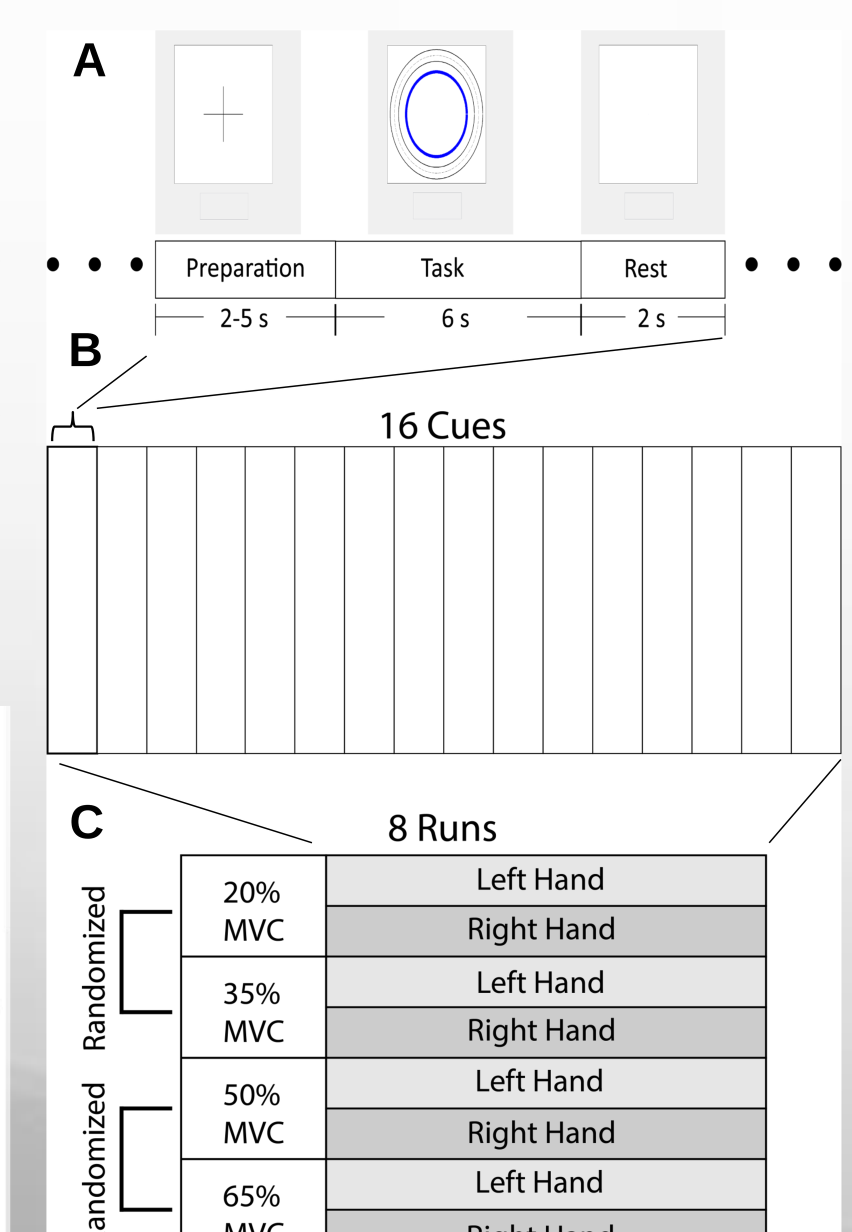

Figure 3. Experimental design. (A) Visual display presented to subject during each cue. (B) 16 consecutive cues make up a run. (C) Each run features each of the four different force targets. Runs alternate between left and right hands at each force target.

Results

Graded EEG Changes During Movement

We first transform the raw EEG to highlight differences between conditions. Signals are filtered into the mu-beta frequency band, and the mean-squared value taken to estimate power in "rest" and "movement" periods (Fig. 4).

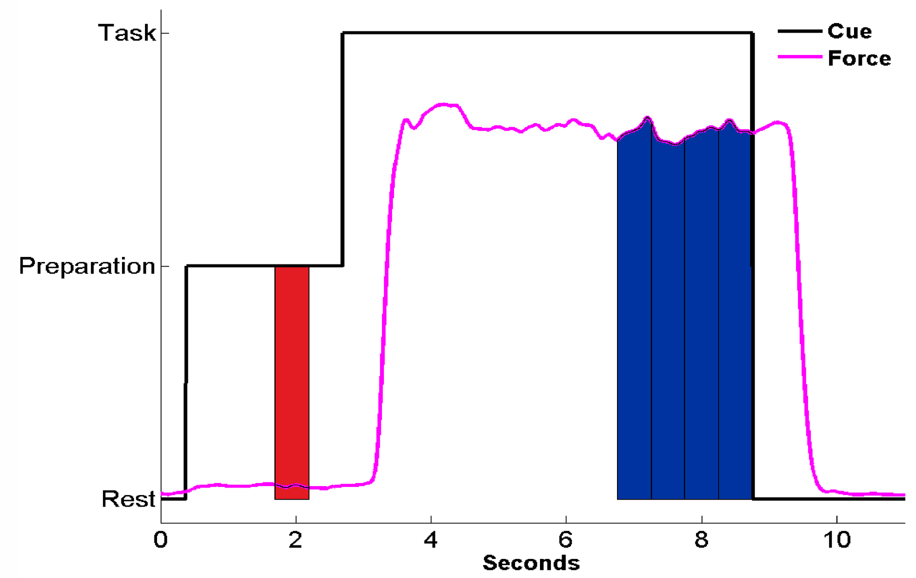

Figure 4. Time periods used for feature extraction. The 0% period (red) consists of EEG data from 1s up to 0.5s before the presentation of the visual cue. The period used to collect EEG from the other classes consists of four 0.5-second windows during the last two seconds of the task period (blue). This was chosen because the subject has usually reached a stable grip force around the target value by that time.

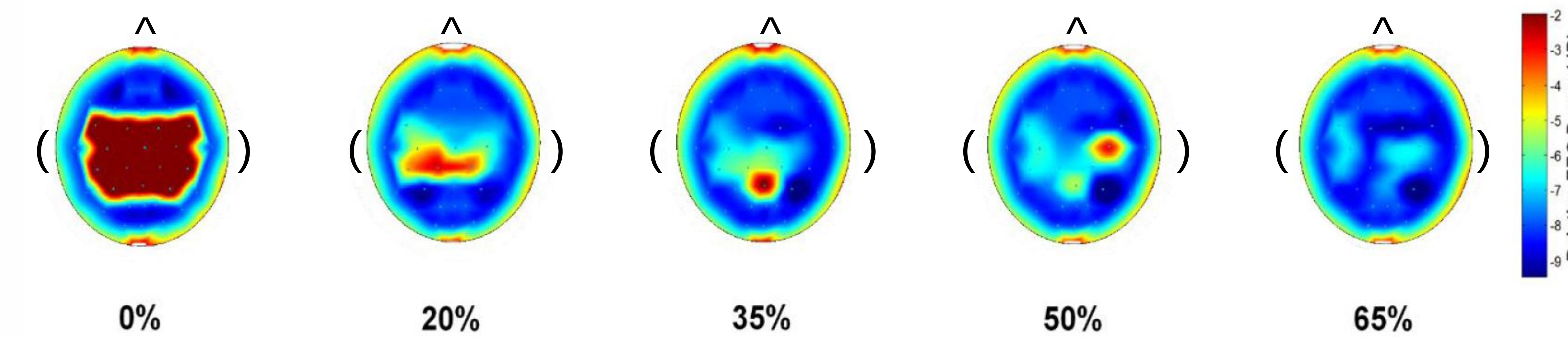

Figure 5. Topographical scalp maps of mean-squared EEG mu-beta power, averaged across cues corresponding to different target MVCs (0, 20, 35, 50, and 65%), for a representative subject. As expected, the rest condition (0% MVC) exhibits high mu-beta power globally. For the non-zero targets, mu-beta EEG power gradually decreases and becomes more spatially diffuse as the target value increases. The spatial differences between conditions provide additional information that could help differentiate between levels of effort in the motor task.

Graded Effort Classification

We saw above that topographical differences in the EEG may be associated with different MVC target forces/motor effort (Fig 5). Next, a statistical classifier is trained to predict applied force. The number of cues/observations in the five classes is balanced and the expected performance of a chance predictor is therefore 1 in 5, or 20%.

A 4-fold cross-validation scheme was used to train and test a linear discriminant (LD) classifier that predicts target MVC from a vector of mu-beta EEG power estimates. While there are numerous machine learning algorithms that could be used, LDA is chosen because it has a relatively low computational load which is convenient in real-time use[2].

Results are stratified by the subject's use of their dominant and non-dominant hand (12 were right-handed, 2 left-handed). Accuracies are reported in terms of a confusion matrix (Fig. 6), with the correct classification along the diagonal. Other common metrics of classifier performance are reported in Table 1.

Matthews correlation coefficient (MCC) is a measure of the quality of classification. Values can range from -1 to +1, where -1 is complete disagreement, 0 is random agreement, and +1 is complete agreement. Eq. 1 shows how to compute this metric from a confusion matrix. MCC for each class is shown in Fig 7. The grand mean value of MCC is 0.41.

$$MCC = \frac{TP\times TN - FP\times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}}$$

TP = true positive
TN = true negative
FP = false positive
FN = false negative

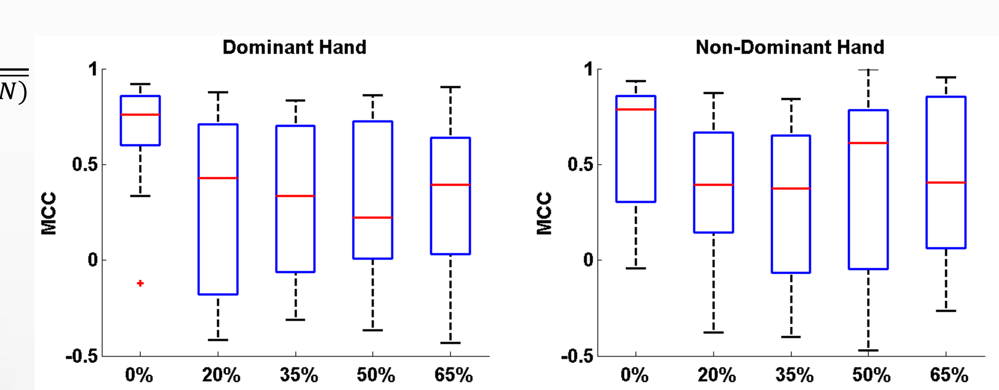

Figure 7. Distribution of MCC for all subjects (n = 14).

Dominant Hand (Actual Class × Predicted Class)

Actual \ Predicted	0%	20%	35%	50%	65%
0%	78% (5)	5% (1)	6% (2)	5% (1)	6% (2)
20%	4% (2)	63% (7)	12% (3)	9% (3)	11% (2)
35%	2% (1)	10% (2)	68% (6)	11% (3)	9% (2)
50%	2% (1)	10% (3)	12% (3)	65% (6)	11% (3)
65%	2% (1)	10% (3)	6% (1)	12% (3)	69% (5)

Non-Dominant Hand (Actual Class × Predicted Class)

Actual \ Predicted	0%	20%	35%	50%	65%
0%	74% (6)	6% (1)	8% (2)	7% (2)	6% (2)
20%	1% (1)	67% (6)	16% (3)	7% (2)	8% (2)
35%	2% (1)	18% (3)	66% (5)	6% (2)	8% (2)
50%	2% (1)	6% (2)	7% (2)	73% (7)	11% (3)
65%	2% (1)	8% (2)	7% (2)	11% (4)	72% (6)

Figure 6. Confusion matrices for the dominant and non-dominant hands reporting mean % accuracy (with standard error) averaged across all subjects (n = 14). Recall that the theoretical chance level of prediction for each class is 20%. Diagonal elements are typically well above this level while off-diagonal elements are below it, which suggests that the classifier is able to discriminate between different levels of exerted force based on EEG features.

Table 1. Measures of model performance by class for all subjects. Values are expressed as mean (SD).

	Dominant Hand			Non-Dominant Hand		
Class	Sensitivity (%)	Specificity (%)	F1 Score (%)	Sensitivity (%)	Specificity (%)	F1 Score (%)
0%	78 (18)	89 (14)	82 (16)	74 (22)	89 (11)	79 (18)
20%	63 (25)	63 (23)	63 (24)	67 (21)	64 (20)	65 (20)
35%	68 (23)	64 (18)	66 (20)	66 (19)	65 (21)	65 (20)
50%	65 (23)	63 (21)	64 (22)	73 (25)	70 (23)	72 (23)
65%	69 (19)	65 (20)	67 (19)	72 (24)	68 (20)	70 (22)

Conclusions and Future Directions

This study aims to improve the ability of BCIs to predict gradations in effort associated with a movement task and thus expand the range of available command signals. Offline analysis shows that the EEG can be used to model and predict five levels of motor effort based on mu-beta suppression using a linear discriminant classifier. The accuracy of the classifier was above chance in all cases, which hints at the potential for its use in a real-time BCI to interactively modulate the user's brain rhythms.

Future Work

- Determine whether the EEG during motor planning and initiation are predictive of intended effort
- Translate the offline model into a real time system
- Investigate adaptive and neuroplastic effects of real-time feedback in the EEG
- Develop a training program which will allow a human subject to operate a device hands-free

Acknowledgments

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