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Using EEG and Machine Learning to Predict Action Goals from Data in the Human Mirror System

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Introduction

The frontal-parietal mirror circuit (FPMC) is active when individuals observe or perform a goal-directed behavior[1]. Evidence in macaques and humans suggest that the FPMC is extremely robust at the point when individuals code the goal of the motor act, enabling an observer to understand an agent's intentions[2, 3]. Recent theoretical hypotheses in the fields of computer science and machine learning suggest that data from the FPMC may have applications in robotics and artificial intelligence[4]. Recently, EEG data has been used to control brain-machine interfaces[5, 6], move a cursor on a computer screen[7], and access a smart phone app[8].

We used EEG to measure mu- and beta-ERD in left and right motor component clusters, while individuals observed and imitated an actor engaging in goal-directed actions where the outcomes were either ambiguous or unambiguous. We employed machine learning algorithms to classify single trial EEG data to determine if participants were observing an action vs. non-movement controls, as well as discriminating between ambiguous or unambiguous goals. These results are discussed in the context of developing a hands-free, non-invasive neural devices that can assist senior citizens with mobility impairments in a Smart Home environment.

Task Design

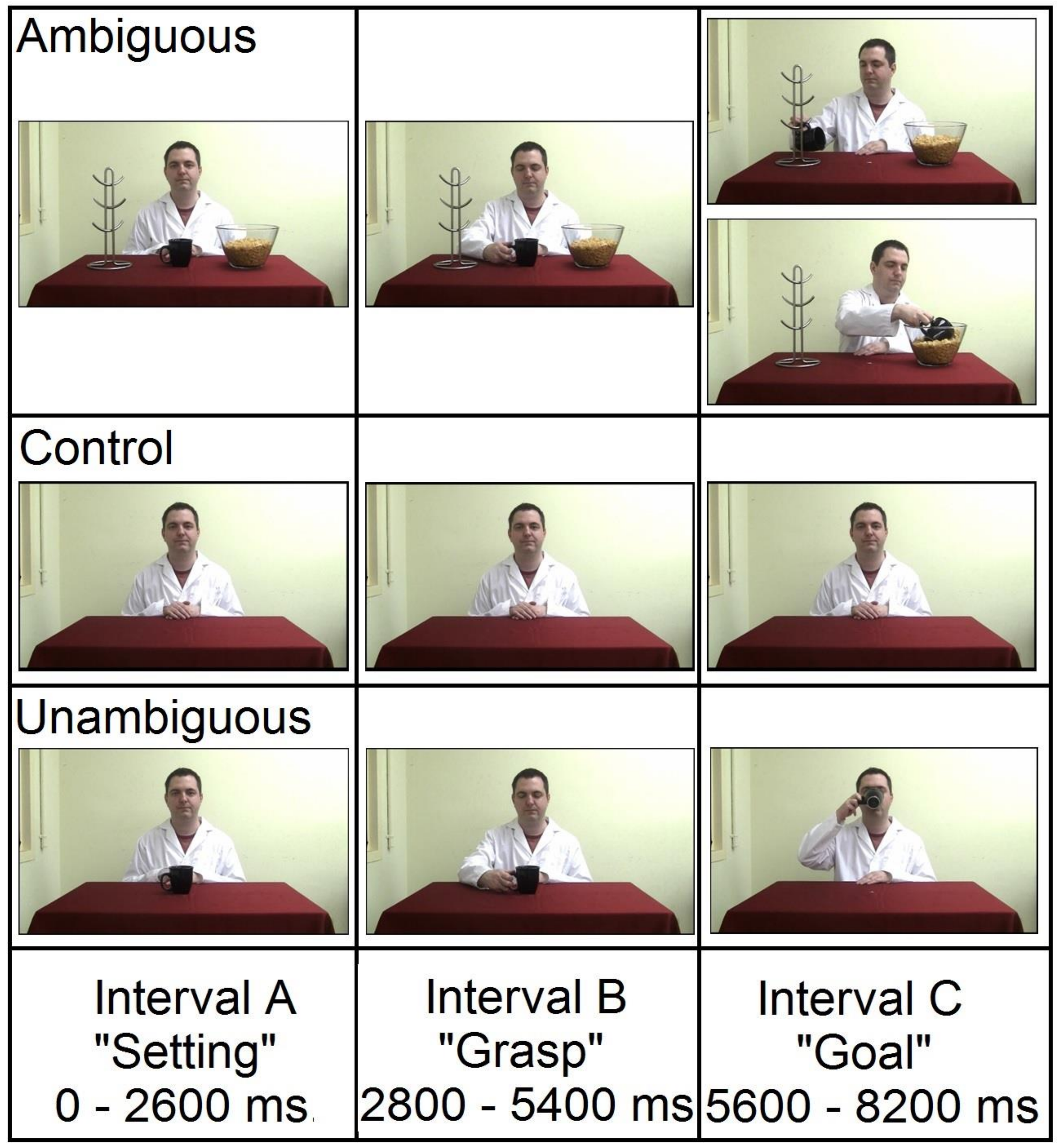

Figure 1. Task. Participants were seated in front of a monitor with a large bowl of cereal to their left, a cup rack to their right, and a coffee mug directly in front of them. Participants observed and imitated the following stimuli: Top row) Ambiguous goal. Actor grasped a cup and used it to scoop cereal from the bowl to his left or placed the cup on a cup rack to his right. Middle) Non-action control. Actor performed no action for entire interval. Last row) Unambiguous goal. Actor grasped a cup and used it to drink. Each interval was preceded by a 2000 ms fixation cross (EEG baseline). Additionally, each interval was separated by a 200 ms fixation cross. A green fixation cross was presented after each trial for five seconds, during which the participants imitated the action. This was followed by a red fixation cross which cued the participants to complete the action and return to the "ready" position. This was followed by a blank screen presented at a jitter of 1500 to 3000 ms.

EEG Results

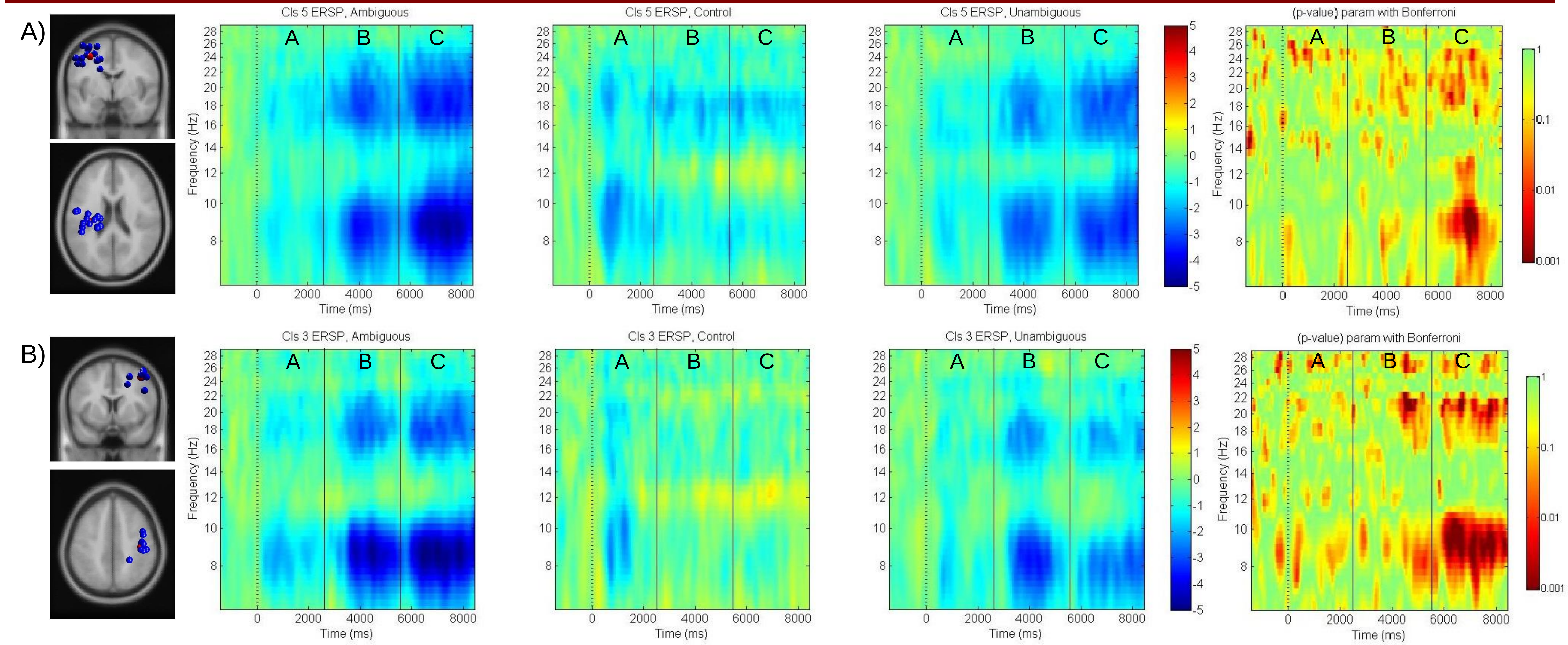

Figure 2. Time frequency plots and statistics for A) left and B) right motor component clusters (within 15% residual variance) across intervals (A, B, and C) for ambiguous, control, and unambiguous conditions. There was a condition x interval interaction in the mu- (8 – 10 Hz) and beta bands (16 – 22 Hz) for both left and right clusters. Mu-ERD during ambiguous conditions was significantly stronger than unambiguous and control during interval C. Ambiguous and unambiguous conditions were significantly stronger than control during intervals B and C in both the mu- and beta-bands.

Methods

Participants:
- 16 right-handed participants

Design:
- 12 blocks – 20 trials each block
  Participants observed and imitated:
  - 96 ambiguous goal videos (scoop cereal or hang mug)
  - 96 unambiguous goal videos (drink from mug)
  - 48 non-action videos (no action)

EEG Analyses:
- 32 Biosemi active electrodes sampled at 256 Hz
- Average reference, and band pass filter (1 - 50 Hz)
- Individual epochs (-2000 to 8200 ms) around onset each trial
  - Movement intervals were removed
- Trials with excessive noise (+/- 100 mv.) were removed prior to 1st ICA pass
- Trials with noisy components (+/- 10 mv.) were removed prior to 2nd ICA pass
- Right and left motor component clusters identified using DipFit2
  - Within 15% residual variance
- Transformed data in frequency domain (4-60 Hz) in 2.25 sec intervals
- Right and left clusters analyzed in mu (8-10 Hz) and beta-bands (16 – 22 Hz.)

Single Trial Classification

- Components were run through a wavelet analysis, isolating the frequencies with the strongest signal to noise ratio for individual trials.
- Individual trials were normalized in reference to the pre-stimulus time period, then the period of time containing each video was averaged out. A set of "lag" features was also created using the difference between the different video intervals. Each feature was binned into 10 discrete values.
- Experiments were run to determine how successful a classification algorithm (Naïve bayes) could perform on a trial by trial basis. The class distribution was balanced using a randomized sub-sampling.
- As an additional experiment, the two action conditions (ambiguous and unambiguous) were combined into one "action" and then compared against the control. The results over several participants is shown on the right in figure 3. Accuracies of up to 80% were obtained.

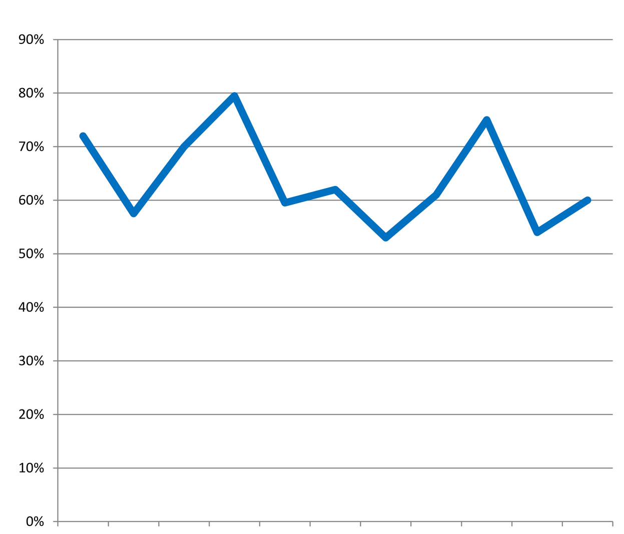

Figure 3. Single trial accuracies of individual participants between control and activity. The 8-10Hz range of a single motor component were used.

Discussion

- Consistent with FPMC activation, we demonstrate that mu- and beta-ERD over left and right motor component clusters is sensitive to detecting motor goals while observing and imitating ambiguous and unambiguous actions. Single-trial EEG data was able to successfully discriminate between ambiguous, unambiguous, and control conditions
  - Mu- and beta-ERD was stronger in interval B for ambiguous and unambiguous conditions versus controls and interval A.
  - Mu-ERD was stronger for ambiguous vs. unambiguous actions during interval C.
  - Additionally, naïve bayes classification yielded up to 80% accuracies when discriminating between action observation and non-movement controls.
    - Most importantly discrimination between all three conditions was slightly 25% above chance
- Previous work has suggested that the FPMC codes for the goal of the action, and not simply its transient components; however, increased activation may also be driven by task complexity[9, 10]
- Further experiments using the entire range of electrodes, components, and frequencies could alleviate the effect of inter-trial variability during machine learning.
- The use of EEG in BMIs to discriminate between brain activity during action planning and observation is critical for the development of non-invasive devices that could be used to detect falls. In order to minimize errors, BMIs would need to be sensitive not just to movement, but a host of other cognitive processes associated with motor activity such as action perception.

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