EEG-Based Early Detection of Self-Initiated Reaching and Grasping Movements Executed with the subject's selected Upper Limb.

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Objective:

This research aims to assess the feasibility of detecting movement intention and classifying the type of reach-and-grasp movement a subject intends to perform, as well as identifying the limb selected for execution, by extracting motor-related information from time intervals preceding movement onset.

Methods:

The electroencephalography signals corresponding to 5 test subjects were acquired, pre-processed, and processed to evaluate the classification of the reach and grasp movement that a subject want to execute and the upper limb with the subject decide to execute that.

- **Experimental protocol:**

An experimental protocol was designed to acquire raw signal data, guiding participants through sequences of visual stimuli comprising attention, execution, and rest phases. Figure 1 displays the images presented to the subjects along with their respective durations. This protocol enabled the collection of electroencephalography data across 300 trials per session, yielding 75 trials per class for each participant.

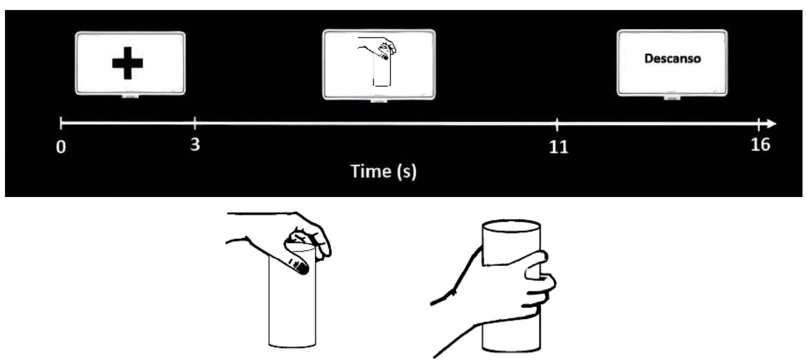

Fig 1. Images used in the experimental protocol.

Each trial, lasting 16 seconds (as shown in Figure 1), was divided into three distinct stages: attention, execution, and rest. In the attention phase, a fixation cross was displayed for 3 seconds, signaling the subject to prepare for the upcoming movement and refrain from blinking or making abrupt movements. Following this, a visual stimulus was presented for 8 seconds, indicating the specific reach and grasp movement to be executed, either vertical or lateral. During the execution phase, subjects were instructed to decide independently when to initiate the movement and which upper limb to use. The trial concluded with a 5-second rest phase, indicated by an image with the word 'descanso,' allowing participants to blink, adjust their position for comfort, and prepare for the next trial, which began with the subsequent fixation cross.

Additionally, four digital signals were recorded from two foam pads, where the subjects' forearms rested during no-movement periods, and from a tubular device that served as the target for the reaching and grasping movements. The tubular device contains sensors that detect the type of movement performed, while the sensors in the foam pads enable detection of the start and end of each movement. These devices use CNY70 reflective sensors, which integrate an infrared emitter and a phototransistor in a package that blocks visible light. The sensors operate effectively within a detection range of 0 to 4.5 mm.

- **Data Collection:**

Data for this research was collected using the high-performance g.HIamp system from g.Tec, which enabled simultaneous recording of 32 EEG channels at a sampling rate of 1200 Hz. The specific electrode configuration employed in this study is depicted in Figure 2.

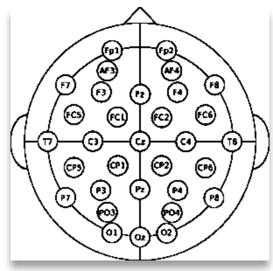

Fig 2. EEG electrodes configuration

Offline Analysis:

CSP features associated with movement intention were extracted from a 1-second time window, starting 1 second before movement onset as detected by the infrared sensors. These features were used for training, fitting, and evaluating the classification model in offline scenarios. Figure 3 illustrates the trial timeline during signal acquisition, with the visual stimulus presented at second 2 marking the beginning of the movement execution phase. The exact onset of the movement is indicated as xxx, as it varies between trials. A leave-one-out cross-validation strategy was employed to fit and test the classification models, where all but one trial were used for training, and the remaining trial was used for testing. This process was repeated until all trials were used for testing.

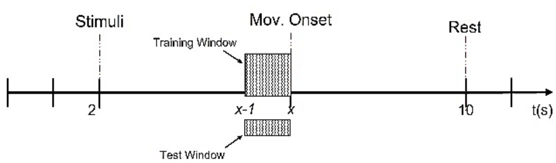

Fig 3. Window to extract the features in offline analysis.

Results:

Figure 4 presents boxplots of the classification accuracies obtained from five subjects across five different scenarios. The first scenario involves the classification of movement onset, comparing a no-movement period with the time window located 1 second before the initiation of the movement, irrespective of the type of movement or the limb used. Following this, the classification of the limb chosen by the subject to execute the movement is evaluated. Finally, the classification of the type of movement is assessed in three distinct scenarios: initially, independent of the limb used, and subsequently, with the analysis conditioned on each specific limb.

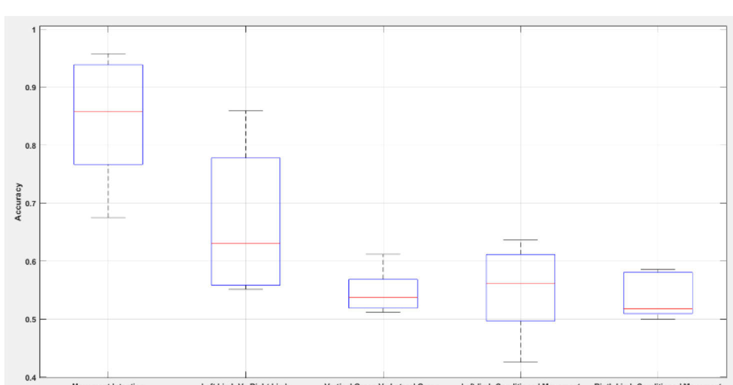

Fig 4. Boxplot of the offline classification accuracies for five healthy test subjects across various scenarios.

Conclusions:

Although the system's performance in classifying different reach-and-grasp movements varies across subjects, the results demonstrate a strong capability for detecting movement onset using brain activity recorded prior to movement execution. Additionally, some subjects exhibited the ability to predict the limb with which the movement would be performed. However, accurately classifying the type of reach-and-grasp movement—whether vertical or lateral—proved challenging with this dataset, even when the analysis was conditioned on the specific limb used.

Future work should aim to increase the number of trials to enhance the robustness of the dataset and simplify the movement types to improve classification accuracy. Furthermore, exploring alternative feature sets may contribute to the development of more effective classification models for distinguishing between different reach-and-grasp movements.