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Predicting User Goals Based on Simulated Brain-Computer Interface Inputs and Robot Sensor Data

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Introduction: Non-invasive brain-computer interfaces (BCIs) provide users with low-dimensional, low-throughout, and inaccurate signals [1,2], leading to difficulties in controlling the many degrees of freedom of a robotic arm. To improve performance, a BCI can be combined with autonomous assistance in a shared control architecture that leverages external sensor data to assist the user [3]. However, to provide this type of assistance, the system needs to understand the goal of the user. Goal determination can be done using an additional input interface (e.g., eye-tracking [4]), but this approach increases system complexity and restricts the user. As an alternative, we explore four algorithms for goal prediction that utilise a single stream of user inputs, and robot sensor data.

Material, Methods, and Results: We used previously collected data from an experiment where twelve participants were tasked with reaching one of five objects in a 3D environment with a robotic arm. We tested two existing algorithms [5] – Amnesic Euclidean (AE) and Euclidean with Memory (EM) – and two new methods – Input Angle (IA) and Input Distance (ID) – for continuously predicting the goal of the user (i.e., which object they wanted to reach). To control robot motion, participants supplied commands using a noisy joystick, the accuracy of which could be set explicitly. This joystick simulated a non-invasive BCI that output four discrete control commands [1,2]. By explicitly setting the accuracy of the interface, the algorithms could be directly compared without variable BCI performance being a confounder.

Predictions were made every 100 ms. AE predicted the object that was closest to the end-effector [5]. EM predicted the most likely object given the distance to each object from the current and starting positions [5]. Assuming the user wanted to move the end-effector directly towards their goal, IA predicted the goal based on the angle between the user input vector and the vector to each object. Similarly, ID predictions used an estimate of the distance that the end-effector would travel towards each object due to the input. At each time step, IA and ID predictions used the entire history of user inputs and end-effector co-ordinates.

Each algorithm was tested on data from successful trials where the interface accuracy was set to either 100% (N=302), 79% (N=303), or 65% (N=297), where 79% and 65% represent typical maximum and mean accuracies of four-class motor imagery BCIs, respectively [2]. Across all three levels of input accuracy, EM, IA, and ID accurately predicted the goal object in greater than 80% (median) of time steps within a trial, while the median proportion of accurate predictions produced by AE was significantly lower (two-sided Mann-Whitney U test, $p < 0.0001$).

Discussion: The high prediction accuracy of EM, IA, and ID showed that heuristic models of behaviour can be used to predict the goal of the user in a reaching task without the need for an additional interface, even when interface accuracy is relatively low. The significantly worse performance of AE demonstrated that the entire history of user inputs and end-effector trajectory should be used to perform predictions.

Significance: When operating a robotic arm using a BCI, predicting which object a user is trying to reach can be used to guide the end-effector, minimising the negative impact of BCI decoder errors on robot motion and making non-invasive BCIs more viable for robotic arm control.

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