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Beyond the control: idle state detection in human intracortical Brain-Computer Interfaces

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Introduction: Brain-computer interfaces based on intracortical recordings (iBCI) have allowed people with tetraplegia to reliably control a computer cursor on a screen and perform actions with a robotic limb [1, 2]. Long-term goals of this technology include the detection of a user's intention to control the interface, allowing automatic switching between volitional neural control of assistive technologies and idle time. Idle state detection has been examined in EEG-based BCI [3] and in intracortical BCI with monkeys [4, 5]. Here, we report the ability to distinguish motor cortical activity in task-related blocks from idle inter-task periods in an individual with tetraplegia using an iBCI.

Methods: The participant in this study (T9) was a 52-year-old man in the BrainGate2 trial with amyotrophic lateral sclerosis. During research sessions, neural signals were recorded from two 96-channel microelectrode arrays (Blackrock Microsystems, Salt Lake City, UT) implanted into his motor cortex. Multi-unit spike rates were extracted (20ms bins) for each channel during centered-out-and-back radial-8 task blocks and during inter-task periods from five sessions in April and May of 2015. Classification performances were computed using linear discriminant analysis with a 10 fold cross-validation. First, on dataset 1 (first 10min of the session), we determined the optimal neural history (T) using the cost function CF below, constrained to a false positive (FP) rate of less than 1%. We then applied the value T on a second dataset and evaluate the positive predictive value (PPV) and negative predictive value (NPV).

$$CF(T) = max \frac{TP(T)}{T\ x\ FP(T)^2 + 1}, \quad \text{with } FP(T) < 1\%$$

Results: Optimal neural history (T) ranged between 2.86 (session E) and 3.90 (session B) seconds (mean±std: 3.30±0.38 seconds). Across all 5 sessions incorporated into this study, linear classification could distinguish idle intertask from cursor control/task periods with a positive predictive value (PPV) and a negative predictive value (NPV) above 98.5%.

Conclusion: In an individual with tetraplegia, idle state could be distinguished from a user's active engagement with high accuracy. Implementing this neural switch online could allow a user to turn the system on and off based on their neural activity only, without the assistance of a caregiver or expert technician. This would also remove undesirable cursor movements on the screen during user's idle periods, providing greater independence and utility for people with severe motor disabilities using iBCI communication.

Significance: We demonstrated that a few seconds of multi-unit spike rates activity could be used to distinguish idle from control periods during intracortical recording in a participant with tetraplegia.

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