Session 334 - Neuroprosthetics: Network and Motor Processing

Add To Itinerary

334.11 / PP1 - Increasing brain-machine interface performance by using discrete state selection with hidden Markov models

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Presenter at Poster
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Poster

Authors

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Disclosures

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Abstract

Communication brain-machine interfaces (BMIs) aim to restore efficient communication to those with neurological injury or disease by decoding neural activity into control signals. These control signals can be analog (e.g., the velocity of a computer mouse) and discrete (e.g., clicking an icon). A major component of a communication BMI is conveying the selection of a target, such as a key on a virtual keyboard. To date, the highest-performance communication BMIs select a target by hovering over it with an analog cursor for a set amount of time (e.g., Nuyujukian et al., IEEE TBME 2015). Although discrete state selection algorithms based on linear discriminant analysis have demonstrated the ability to decode a discrete "click" state to select the target (e.g., Kim et al., IEEE TNSRE 2011), these algorithms do not perform as well as simply hovering over the target for a set amount of time (Gilja*, Pandarinath*, et al., Nature Medicine 2015).
A better approach to achieving reliable, accurate and fast target selection may be with hidden Markov models (HMMs; Nuyujukian et al., SFN 2012). We performed closed-loop BMI experiments with two monkeys, where we decoded threshold crossings from intracortical multielectrode arrays implanted in primary motor cortex and dorsal premotor cortex. We incorporated an HMM to perform discrete state selection in parallel with a continuous decoder (ReFIT-KF; Gilja*, Nuyujukian*, et al., Nature Neuroscience 2012). We found that both monkeys were able to achieve significantly higher communication performance when targets were selected with the HMM rather than hovering over the target (13.9% increase in achieved bitrate in Monkey J, 4.2% in Monkey R, $p < 0.01$). Further, we found that the transition model of the HMM was crucial to achieving this performance. Specifically, we observed that the HMM performed significantly better than a quadratic discriminator using only the emissions process of the HMM (14.8% increase in achieved bitrate in Monkey J, 16.5% in Monkey R, $p < 0.01$). Finally, we found that discrete state selection with an HMM resulted in the highest achieved peak-bitrates we have measured for these monkeys across years of experimental sessions (6.5 bps for Monkey J, 5.7 bps for Monkey R). This parallel ReFIT-KF + HMM decoding approach has been translated in human clinical trials, achieving the highest-reported typing rates (Pandarinath et al., SFN 2014) and allowing intuitive use of an Android tablet (Nuyujukian et al., SFN 2015). Together, these results demonstrate that high-performance discrete state decoding with HMMs can be beneficially incorporated into a communication BMI

to achieve new state-of-the-art levels of performance.