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Presentation Abstract

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Presentation Title:	A robust and high-performance brain-machine interface using a nonlinear recurrent neural network trained with years of neural data
Location:	WCC Hall A-C
Presentation time:	Sunday, Nov 16, 2014, 1:00 PM - 5:00 PM
Presenter at Poster:	Sun, Nov. 16, 2014, 3:00 PM - 4:00 PM
Topic:	++D.18.d. Neuroprosthetics: Control of real and artificial arm, hand, other grasping devices
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Abstract:	Clinically viable brain-machine interfaces (BMIs) must not only perform well, but should also be robust to across-days and within-day changes in the neural data. Linear techniques, including state-of-the-art Kalman filter-based decoders (e.g., Gilja et al., 2012) are not well-suited for dealing with non-stationary data because their modeling assumptions result in underfitting. Thus, although neural recordings from the previous months to years may be available, these decoder architectures do not adequately make use of the richness and variance of these datasets. Our goal was to overcome this by using nonlinear techniques (e.g., Sussillo et al., 2012). We present a novel nonlinear architecture for BMI use that is constructed to improve

robustness: the multiplicative recurrent neural network (MRNN, Sutskever et al., 2011). The nonlinearities in the MRNN enable improved robustness by (1) leveraging multi-year training datasets and (2) training with explicitly perturbed neural data. We report both performance and robustness results superior to the current state-of-the-art. We implanted one monkey with 96-electrode arrays in both primary motor and dorsal premotor cortex and collected neural data across two years of reaching experiments. We trained the MRNN using a merged training set comprising approximately 120 datasets (60,000 trials) collected from 08/31/2012 until the day prior to experimentation in 03/2014. To train the decoder to be robust to unexpected neural changes, we perturbed the neural training data by randomly increasing or decreasing spike counts. We first evaluated if the MRNN could outperform an existing state-of-the-art BMI decoder, the FIT-KF (Fan et al., 2014), which was trained with data collected on the day of experimentation. The MRNN acquired targets faster than the FIT-KF (5.7% more targets per minute (tpm), $p < 0.05$). We next evaluated the robustness of the MRNN and FIT-KF to an unexpected loss of channels. The MRNN sustained better performance than the FIT-KF in the face of channel loss (52.1% more tpm across conditions, $p < 0.05$). Finally, we evaluated the robustness of the MRNN and FIT-KF to a natural sampling of neural non-stationarities. Both decoders were trained without access to the last four months of data and were then evaluated day after day, sampling naturally occurring neural differences between distant training days and the evaluation day. The MRNN substantially outperformed the FIT-KF (105% more tpm, $p < 0.05$). These results demonstrate that a nonlinear decoder that leverages a diversity of training data can substantially increase the robustness and performance of a BMI.

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