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Optimizing Decoder Dynamics Strength for Closed-Loop Brain-Computer Interfaces

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Introduction: The use of artificial neural networks for decoding movement from neural signals has led to recent improvements in closed-loop brain-computer interface (BCI) control [1, 2]. Since neural signals typically have low signal-to-noise ratio (SNR) for task relevant information, the decoder must find the optimal balance between relying on noisy inputs versus prior knowledge of movement patterns. However, open-loop accuracy does not directly predict closed-loop performance [3, 4] making it challenging to design neural network decoders that optimize this balance. Here we investigated a novel decoder loss function, which allows for tuning the degree of decoder memorization, on closed-loop performance.

Materials, Methods and Results: We trained recurrent neural network (RNN) decoders to predict finger kinematics from spiking-band power features. RNNs were trained using a loss function that combined mean-squared error (MSE) with additional, tunable weight penalties that varied the decoder's reliance on learned task dynamics versus neural inputs. By tuning the penalties, we trained decoders with reduced reliance on neural inputs ("strong dynamics") or with increased reliance on inputs ("weak dynamics"). Additionally, we created a "dynamics strength" metric that quantifies the ratio of the current hidden state's sensitivity to its previous hidden state (derivative with respect to the prior hidden state) versus its sensitivity to neural inputs (derivative with respect to neural inputs), averaged over time. Using simulated data from an open-loop 3-target task with log-linear tuned channels, weak and strong dynamics decoders had similar kinematic decoding accuracies (correlations of 0.94 and 0.97, respectively) despite having largely different dynamics strengths (1.01 versus 5.75, respectively), suggesting different internal decoding mechanisms (Figure 1). We tested both decoders in closed-loop trials across three sessions with one rhesus macaque who was implanted with Utah arrays in motor cortex and trained to perform a 1-degree-of-freedom (DoF) continuous target-acquisition task. Both weak and strong dynamics decoders had 100% success rate, however, the smoothness of decoder movements increased as dynamics strength increased. When dynamics strength was increased further by training with a 100x instead of 10x weight penalty, the decoder failed to generalize to produce corrective movements resulting in a decreased success rate of 83%.

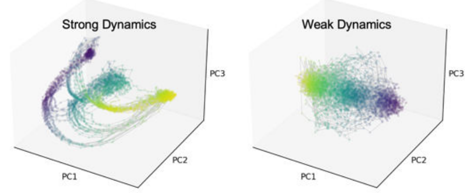

Figure 1: *PCA of the hidden state of GRU decoders trained with strong vs weak dynamics, on a 3-target task. Each dot is one time-point, and color represents the output position. Both decoders have similar accuracy but have visually different state trajectories.*

Conclusion: These results suggest that decoder generalization can be tuned using the loss function, which may be an important tool as BCIs expand to more complex tasks. Future work may investigate the optimal decoder dynamics strength for closed-loop control with varied SNR neural signals, and how this impacts the choice of decoder architecture.

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References:

[1] Willsey, M.S., Shah, N.P., Avansino, D.T., Hahn, N.V., Jamiolkowski, R.M., Kamdar, F.B., Hochberg, L.R., Willett, F.R., Henderson, J.M., 2024. A real-time, high-performance brain-computer interface for finger decoding and quadcopter control.

[2] Costello, J., Temmar, H., Cubillos, L., Mender, M., Wallace, D., Willsey, M., Patil, P., Chestek, C., 2023. Balancing memorization and generalization in RNNs for high performance brain-machine Interfaces, in: Oh, A., Naumann, T., Globerson, A., Saenko, K., Hardt, M., Levine, S. (Eds.), Advances in Neural Information Processing Systems. Curran Associates, Inc., pp. 7462–7474

[3] Cunningham, J.P., Nuyujukian, P., Gilja, V., Chestek, C.A., Ryu, S.I., Shenoy, K.V., 2011. A closed-loop human simulator for investigating the role of feedback control in brain-machine interfaces. Journal of Neurophysiology 105, 1932–1949.

[4] Deo, D.R., Willett, F.R., Avansino, D.T. et al. Brain control of bimanual movement enabled by recurrent neural networks. Sci Rep 14, 1598 (2024)

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