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Presentation Abstract

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Presentation Title: Increasing brain-machine interface performance by modeling neural population dynamics

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Abstract: State-of-the-art brain-machine interfaces (BMIs) drive prosthetic devices with neural activity by modeling the correlations between neural firing rates and movement. These BMIs, however, do not account for temporal structure in the population neural activity--that is, they do not model how the population activity evolves over time. Recently, it was shown that populations of neurons in premotor (PMd) and primary motor cortex (M1) exhibit dynamical structure during reaching (Churchland, Cunningham et al., 2012). This dynamical structure describes the temporal evolution of a low-dimensional neural state: the future neural state can be estimated from the present state given the dynamics it obeys. Modeling these dynamics may be important for increasing the performance of BMIs, where decodes occur over noisy single trials. To combat single trial noise, one may be able to use dynamics to compute a prior estimate of the future neural state. This augments the estimation of the neural state to include dynamical information, in contrast to using only instantaneous neural observations or estimating kinematic dynamics (as in velocity Kalman filters). For example, if the modeled neural state exhibits rotational behavior through state space, augmenting the BMI with this dynamical information may smooth over unexpected neural state trajectories, such

as expansive motion, resulting from noisy instantaneous observations.
To test this idea, we incorporated the neural dynamics of a population of spiking channels into an online 2D-cursor control BMI. We evaluated the performance of the BMI when neural dynamics were modeled versus when neural dynamics were not modeled. We modeled the observations of the BMI, which were binned threshold crossings measured from electrode arrays in PMd / M1, as the observations of a latent state linear dynamical system (LDS) learned via expectation maximization (Ghahramani & Hinton, 1996). We then regressed the state of the LDS, which obeyed modeled dynamics, to predict the position and velocity of a 2D-cursor. As a control experiment, we also regressed smoothed binned spike counts to predict the position and velocity of a 2D cursor. We found that when the population dynamics were modeled, the BMI achieved 83% and 31% higher performance (bitrate) in Monkey L and J, respectively ($p < 0.001$). We also recognize that this method could be combined with other state-of-the-art techniques; for example, the intention estimation corrections of the ReFIT-KF algorithm (Gilja, Nuyujukian et al. 2012) are a complementary innovation. This suggests that modeling the dynamical structure in neural data may be important for further increasing the performance of BMIs.

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