Neural decoding of goal-directed movements using a linear state-space model with hidden states

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Decoding algorithms, which translate neural activity into command signals for external devices such as robotic limbs and computer cursors, are a key component of neural prosthetic devices. Classically, a linear state-space model, with bayesian inferencing methods, has been used as it enables real-time implementation. This model is based on a linear Gaussian approximation between neural firing rates and hand motion, and an autoregressive representation for the hand kinematics over time. In this work we suggest two key modifications to the classical model in order to improve decoding accuracy.

Firstly, the classical model does not account for kinematic or kinetic terms, such as joint angles at shoulder and elbow, muscular activation, or other behavioral state such as the subject's attentional level. All these features, however, are closely related to the brain-controlled, muscle-executed hand movement. We address this limitation by adding a hidden state to the Kalman filter model to represent these features. We assume that the observed neural firing rate is linearly related to the hidden state, and furthermore, we allow the dynamic of the hand state to impact the dynamics of the hidden state, and vice versa. The parameters in the model can be identified by the conventional Expectation-Maximization algorithm.

In our second modification to the classical approach we condition the estimated trajectory on available end-point information. In most clinical settings, the patient interacts with an external device by choosing one of a few targets on the screen. Since we know the location of these targets in advance we can use this information in conjunction with the estimate obtained from the Kalman filter to obtain a more accurate estimate of intended hand-position. This updated estimate is obtained by using forward-backwards computations familiar from the theory of the Kalman filter.

We tested our method using data recorded from a Macaque monkey executing a visuo-motor task with one of its arms. The data consists of hand-position and 125 simultaneously recorded single-units. We found that the decoding accuracy is an increasing function of the dimension d of the hidden state. For example, when $d = 1$, the improvement in the mean-squared error (cm^2) is 5%, whereas for $d = 3$, the improvement reaches about 16%. Furthermore conditioning on the target can increase the accuracy by up to 45%.

Table 1: Decoding error (cm^2)

	Classical Model	1-d hidden state	2-d hidden state	3-d hidden state
Without target information	8.2	7.8	7.1	6.9
With target position information	4.6	4.3	3.8	3.7

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