Motor Cortical Decoding Performance Depends on Controlled System Order

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***Abstract*— Recent advances in intracortical brain-machine interfaces (BMIs) for position control have leveraged state estimators to decode intended movements from cortical activity. We revisit the underlying assumptions behind the use of Kalman filters in this context, focusing on the fact that identified cortical coding models capture closed-loop task dynamics. We show that closed-loop models can be partitioned, exposing feedback policies of the brain which are separate from interface and task dynamics. Changing task dynamics may cause the brain to change its control policy, and consequently the closed-loop dynamics. This may degrade performance of decoders upon switching from manual tasks to velocity-controlled BMI-mediated tasks. We provide experimental results showing that for the same manual cursor task, changing system order affects neural coding of movement. In one experimental condition force determines position directly, and in the other force determines cursor velocity. From this we draw an analogy to subjects transitioning from manual reaching tasks to velocity-controlled BMI tasks. We conclude with suggested principles for improving BMI decoder performance, including matching the controlled system order between manual and brain control, and identifying the brain's controller dynamics rather than complete closed-loop dynamics.**

I. Introduction

Brain-machine interfaces (BMIs) convert movement intentions, represented in recorded cortical activity, into commands for an external system. Here we are concerned with those designed to provide continuous position control of a computer cursor or robotic arm.

BMIs are often developed by first identifying the relationship between native limb movement and cortical activity [2], [4], [6], [11]. This is historically driven by assumptions of firing rate coding for movement according to cosine tuning functions [3]. The identified model can be used to implement a state estimator which predicts limb kinematics using cortical activity. Next, decoded limb velocity is mapped to cursor velocity, adding an integrator to the external task dynamics compared to the manual control case.

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This approach has been used by several research groups [2], [4], [6], [11], in particular when the identified model is a linear state space system and a Kalman filter is used as the state estimator. In this paper, we revisit the modeling assumptions underlying the use of Kalman filters, and suggest alternative interpretations for the identified models. We consider that manual reaching tasks involve dynamics that are quite different from velocity-controlled BMI tasks. This leads us to question whether a change to the controlled system will result in changes to the cortical representation of task state, which could violate the expectation of a decoder-based BMI.

In Section II, we motivate our hypothesis by reviewing the use of system identification and Kalman filters in BMI studies. We then describe a set of experiments in Section III which allow us to test this hypothesis in Section IV. Finally, in Section V we discuss the implications of our findings for BMI design, and suggest areas for future work to improve our understanding of how cortical task representation changes across different manual tasks and BMI control.

II. Background

A. Modeling Approaches

The basic system model used for Kalman filters in many BMI studies is the discrete-time state-space system defined by

$$\mathbf{x}[t+1] = \mathbf{A}\mathbf{x}[t] + \mathbf{w}[t] \quad (1)$$
$$\mathbf{y}[t] = \mathbf{C}\mathbf{x}[t] + \mathbf{q}[t] \quad (2)$$

where $\mathbf{x}[t]$ represents task or limb state including position and one or two derivatives; $\mathbf{y}[t]$ represents recorded cortical activity; and the system is driven by Gaussian noise terms $\mathbf{w}[t] \backsim \mathcal{N}(0, \mathbf{W})$ and $\mathbf{q}[t] \backsim \mathcal{N}(0, \mathbf{Q})$. The state $\mathbf{x}[t]$ is intended to capture actual kinematic task states during manual control, and intended task states during BMI-mediated control. This paradigm was first applied in [11].

There are multiple problematic assumptions implicit in this modeling approach, some of which have been addressed by more recent innovations. First, the only external inputs to the system are noise; no control action by the subject is explicitly represented. Additionally, it assumes that the brain has a perfect observation (or estimate, $\hat{\mathbf{x}}[\mathbf{t}]$) of task state, i.e. $\hat{\mathbf{x}}[t] = \mathbf{x}[t]$. The problem of assuming perfect estimation is in part driven by known delays in neural sensory processing.

One approach for incorporating these latencies into the model is to fit a time shift between external task state and cortical activity, as in [11]. In that study, the authors assume a time lag between neural activity and kinematic state, and test which positive value results in the best reconstruction based on mean-squared error (MSE) and correlation coefficient (R^2).

More recent studies have explicity incorporated assumptions about task state estimation in cortex into the models used with Kalman filters. In [4], the standard Kalman filter update algorithm is modified to reflect an assumption that the subject is able to eliminate internal model uncertainty about cursor kinematic states at each timestep. This is implemented mathematically by setting the position estimate uncertainty to zero, termed 'causal intervention'. An additional change to the standard Kalman filter in [4] and later work [2] is assigning some model parameters based on assumptions about dynamics. For example, integrated velocity should perfectly describe position, so necessary entries in $\mathbf{A}$ are set to zero after performing an unconstrained model fit.

A further refinement to the modeling of visual processing combined with state estimation in cortex is presented in [5]. Here, cortical state estimates are assumed to involve forward prediction from delayed visual information, and the appropriate prediction interval is identified from data recorded during BMI-mediated tasks. This can be performed under the assumption that neural activity is based on the brain's immediate movement intentions, in turn are based on immediate state estimates. Importantly, that study's results show that a predictable error exists between ground-truth task state and instantaneous cortical estimates of task state.

B. Partitioning the Model

The closed-loop task dynamics captured by $\mathbf{A}$ may conceal separable forward task dynamics and feedback control dynamics. For example, consider the simple case of full-state feedback, wherein the controller applies a gain to each component of the task state vector, as shown in Figure 1.

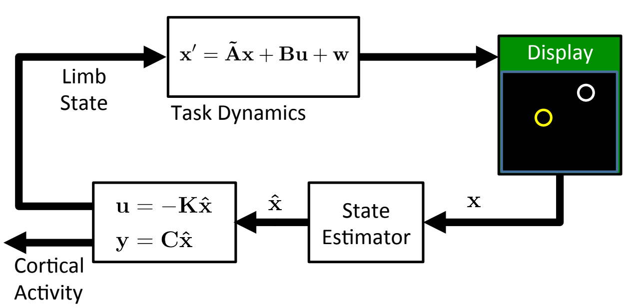

Fig. 1. Block diagram of a full-state feedback model of manual cursor control. The task state represents the cursor kinematics, and the control input is muscle force. Note that the cortical feedback controller only has access to its estimate of cursor state.

Under this scenario, and assuming perfect cursor state estimation, the autonomous dynamics of the closed-loop system are given by $\mathbf{A} = (\tilde{\mathbf{A}} - \mathbf{BK})$. The control policy of the brain is captured by $\mathbf{K}$, and is separate from the control interface, $\mathbf{B}$, and autonomous task dynamics, $\tilde{\mathbf{A}}$. If either component of the task dynamics changes, then the control gains may also change, and the closed-loop autonomous dynamics captured by $\mathbf{A}$ may change as well. Some changes to the values of these parameters can in principle be perfectly compensated for by the brain, but studies varying control-display gain in manual cursor positioning tasks reveal that this is not done [1], [10]. However, changes to the task system order, such as by changing the form of $\mathbf{B}$ and the mapping of control input to task kinematics, will inevitably cause changes to the closed-loop dynamics. Such changes cannot be compensated for by any change in control strategy.

The simple full-state feedback model can capture only proportional control policies; it cannot capture feed-forward control actions resulting from path planning by the subject, nor can it capture more complex policies such as integral control. A much wider variety of feedback controllers can be captured if the controller is assumed to have its own dynamics and internal state variables. All of these possibilities, save the full-state feedback case, cannot be captured by closed-loop dynamical models assumed to have internal states equal to the task kinematics.

In this study, we test whether adding an external integrator to the task dynamics changes cortical representation of task state during manual control.

III. Methods

A. Electrophysiology

A macaque is implanted with dual 96-channel microelectrode arrays (Blackrock Microsystems, Salt Lake City, UT), bilaterally in motor cortex, which are connected to a 128-channel Cerebus neural signal processor (Blackrock). Manually set time-voltage criteria are used for online spike sorting, which is recorded at 30KHz for offline analysis. Custom LabVIEW software (National Instruments) is used to implement the BMI decoding algorithm and behavioral tasks. We conduct experiments in a primate behavior booth outfitted with a computer monitor, buzzers, and a computer-controlled feeder containing apple sauce. The animal's arm is situated in a custom 2-DOF near-isometric manipulandum. A computer monitor, is 30 cm x 23 cm (W x H), is located 28 cm in front of the animal's head. A neural decoding algorithm and cursor task operate at a sampling rate of 60Hz, with the display refreshed at 30Hz. The BMI system input-output latency is measured to be about 50ms. All procedures were approved by the University of Washington Institutional Animal Care and Use Committee.

B. Experiment Design

The manipulandum is used for task training and to measure neural correlates of motor activity. This eliminates the possibility that neural activity is accounted for by tuning functions to limb kinematics or dynamics, since there are minimal postural changes.

The animal performs two variations on a 2D "pinball" task: one in which manipulandum torque is mapped to cursor velocity (*velocity control*), and one in which manipulandum torque is mapped directly to cursor position (*position control*). Thus, the task dynamics of velocity control are a single integrator, while the task dynamics under position control are a one-to-one mapping with no internal state. We compare these experimental conditions with those in a BMI training and testing paradigm in Figure 2.

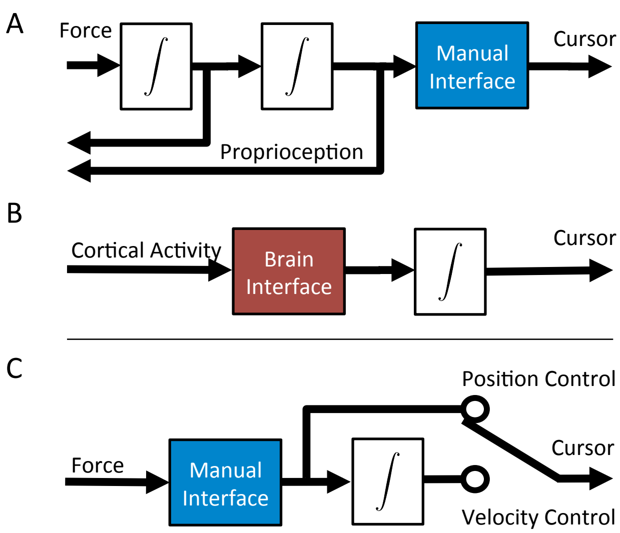

Fig. 2. A) During training for BMI implementation, second-order task dynamics are created by the physical (limb) system and are natively observable to the subject via proprioception. B) During BMI-mediated control, a new integrator is added by decoding velocity. C) Experimental variations tested in the present study using an isometric control interface. Force is mapped either directly to position or to cursor velocity during manual control, and cursor velocity is decoded from cortical activity offline.

Blocks of tens of trials are performed under a given condition, with short breaks and other conditions interspersed between position and velocity control blocks. This allows us to test whether the task dynamics, in particular system order, effect cortical representation of task while visual task feedback is held constant. If cortical representation changes, then this would suggest that task dynamics should be held constant between decoder training and BMI control.

IV. Results

We aim to determine whether adding an integrator to external task dynamics degrades decoder performance. To do this, we identify cortical coding models using position- or velocity-controlled trial data, then test those models against velocity-controlled trials from the same experimental session. This is analogous to the integrator added to external task dynamics in BMIs which are controlled by decoded velocity estimates.

We use two types of models to estimate task kinematics from neural activity: linear estimators, based on the population vector algorithm [3], and Kalman filters. The linear estimator has no built-in assumptions about closed-loop task dynamics, and only identifies the relationship between instantaneous dynamic state and cortical activity. The state-space model used in the Kalman filter does explicitly model closed-loop task dynamics, as discussed above. For consistency with the decoding paradigm of BMI design, we assessed model power by predicting task state based on cortical activity.

Before performing system identification or testing model prediction, we filtered spike counts (recorded at $60Hz$) and cursor states with a Gaussian filter, $\sigma = 0.05s$, and decimated the sampled data by a factor of three. As recommended in [8], this restricts identification and prediction to the input/output relationships we believe exists in the data and filters out process noise in the spike data. Additionally, we truncated trajectories to begin at the first time at which the cursor moved towards the target, thus eliminating undirected movements while the subject was still reacting to a new task presentation. Model identification and trajectory reconstruction were then performed in error coordinates, so that the modeled closed-loop system would be stable to the origin. Example trajectory reconstructions are shown in Figure 3.

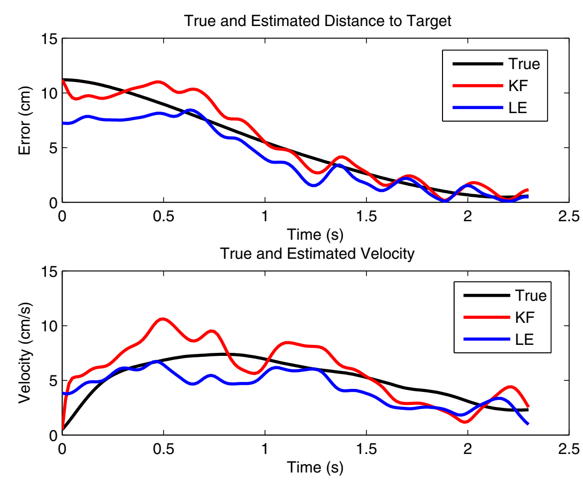

Fig. 3. Magnitude of cursor position estimate error *(top)* and velocity estimate error *(bottom)* during a velocity-controlled trial. KF denotes Kalman filter prediction, while LE denotes linear estimator prediction.

We identify a model for a given block of trials, then evaluate its performance with all other velocity-controlled trial blocks in the same experimental session. We test models by evaluating R^2 coefficients for reconstruction of cursor position and velocity for a given block of test trials. In this way we control for time variability of neural coding. We group resulting model performance according to the task type we used to identify the model. The results of this process are shown in Figure 4.

The significant change in model performance across task system order supports our hypothesis that changes in cortical representation of the task occur. Recall, however, that this decoding approach includes assumptions about closed-loop task dynamics, which are violated by a change in task system order.

We next repeat the analysis using linear estimators, fit using a simple linear regression of kinematics against cortical activity. The use of a linear estimator removes any as-

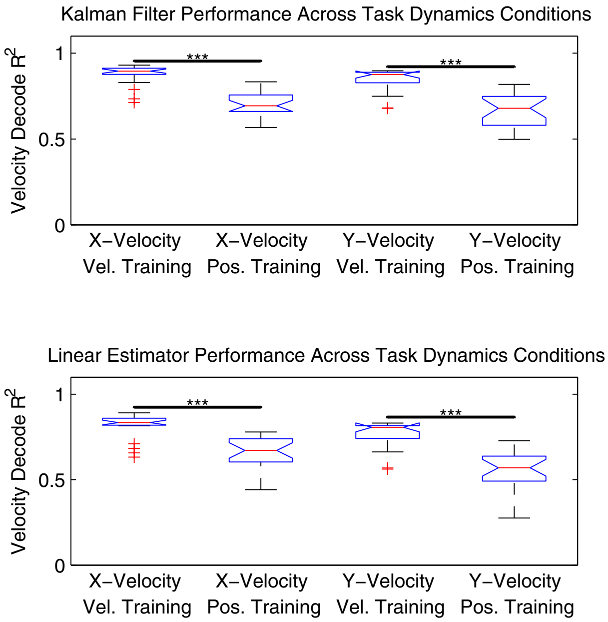

Fig. 4. Cursor velocity decoder performance across conditions. Each distribution is the correlation coefficients for performance of a model identified under the task type in the label, tested against trials of velocity control. The results indicate that velocity prediction error increases if the task condition changes between model identification and testing. In particular, we see a significant (***$p < 0.001$, Wilcoxon rank-sum test) decrease in performance when a decoder identified from velocity-controlled trials is applied to position-controlled trials.

sumptions about closed-loop dynamics, and therefore should specifically decode cortical representation of instantaneous task state in isolation. These results suggest that cortical representation of task state is in fact changed by a change in the controlled system order.

V. Discussion

We have shown that cortical decoding performance of task state changes as a consequence of changes to the controlled system order, without changing the control interface. This change is evident even with a linear decoding algorithm, which has no implicit assumptions about closed-loop task dynamics.

Prior studies have shown that motor cortical neurons adapt their tuning properties in response to changes in directional mapping of force [7] and directional profile of forces required for movement [9]. In our study, the experimental manipulation added task dynamics unobservable via proprioception, requiring the subject to use visual observation alone to estimate task state. This is more analogous to the transition from direct manual cursor control to velocity control of a cursor using decoded cortical signals, as is done in BMI paradigms.

This suggests that the change in task dynamic system order, such as when mapping estimated velocity to commanded cursor velocity during BMI control, may cause substantial changes in cortical task representation. This would effectively invalidate the identified model, causing poor performance. This is how current decoding efforts are being performed [2], [4].

Recent studies have shown remarkable performance improvements via closed-loop decoder adaptation (CLDA) after initializing a BMI using an identified dynamic model of manual control [2]. It is possible that learning rate could be substantially improved, even under the CLDA paradigm, by matching the controlled system dynamics as much as possible between manual and BMI-mediated control.

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