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A stabilized dual Kalman filter for adaptive tracking of brain-computer interface decoding parameters

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***Abstract*—** Neural prosthetics are a promising technology for alleviating paralysis by actuating devices directly from the intention to move. Typical implementations of these devices require a calibration session to define decoding parameters that map recorded neural activity into movement of the device. However, a major factor limiting the clinical deployment of this technology is stability: with fixed decoding parameters, control of the prosthetic device has been shown to degrade over time. Here we apply a dual estimation procedure to adaptively capture changes in decoding parameters. In simulation, we find that our stabilized dual Kalman filter can run autonomously for hundreds of thousands of trials with little change in performance. Further, when we apply our algorithm off-line to estimate arm trajectories from neural data recorded over five consecutive days, we find that it outperforms a static Kalman filter, even when it is re-calibrated at the beginning of each day.

I. Introduction

Brain-computer interfaces (BCI) can restore movement to those who are paralyzed by providing behavioral output directly from the intention to move, bypassing defective neural transmission and muscle activation [7], [11], [13]. Most BCIs require a calibration session to compute decoding parameters that define how recorded neural activity will translate into movement of the device. Calibration is necessary to build models of how neural firing rates are modulated by desired movement. However, these calibrations are not particularly stable: decoding parameters estimated in one session will often not apply even on the next day [2]. This instability could be due to electrode drift, changes in background noise, or changes in the neural tuning curves themselves [10]. Regardless of its source, the daily re-training of the decoding algorithm necessary to achieve optimal performance is a major factor limiting the clinical utility of this technology.

Some approaches have previously been proposed to combat BCI decoder instability. In [8], Bayesian regression self-training methods were used to update parameters based on estimates from an unscented Kalman filter. In [12], a kernelized auto-regressive moving average was employed to change the decoder over time. Here we introduce an alternative method, based on a dual-Kalman filter, as a simple extension to commonly used BCI decoders. Dual-estimation can be sensitive to self-training, which appears to also be a problem in our simulations. However, we find that two simple heuristics can be implemented to substantially improve the estimation stability. We find in both simulation and off-line analysis that our stabilized dual Kalman filter remains robust to parameter drift over long time scales.

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II. Decoding Model

A. Kalman Filter: Fixed Decoding Model

Typical BCI decoders are based on the Kalman filter, due to its rigorous theoretical framework and easy implementation [14]. In this framework, limb state is treated as an unobserved vector that evolves over time. We define the state vector at time t, denoted as $\boldsymbol{x}_t$, as the desired end-point velocity of the effector augmented by 1, i.e., $\boldsymbol{x}_t = \left(\boldsymbol{v}_t^{\mathsf{T}}, 1\right)^{\mathsf{T}}$. The state transition from one time-step to the next is assumed to follow a random walk model (Eq. 1). The neural firing rate for neuron i at time t, denoted as $y_t^{(i)}$, is treated as an observation of this state vector (Eq. 2):

$$\text{Evolution:} \quad \boldsymbol{x}_{t+1} = \boldsymbol{x}_t + \boldsymbol{\omega}_t,\ \boldsymbol{\omega}_t \quad \mathrm{N}(0, W) \tag{1}$$

$$\text{Observation:} \quad y_t^{(i)} = \boldsymbol{\beta}^{(i)\mathsf{T}} \boldsymbol{x}_t + \epsilon_t^{(i)},\ \epsilon_t^{(i)} \quad \mathrm{N}(0, \sigma^2) \tag{2}$$

where $\boldsymbol{\beta}^{(i)}$ are the linear tuning parameters corresponding to neuron i, and $\boldsymbol{\omega}_t$ and $\epsilon_t^{(i)}$ are zero mean Gaussian noise with covariance matrix W and variance σ^2, respectively.

While the Kalman filter has successfully been used to achieve proficient closed-loop BCI control [6], [14], the implicit assumption that the linear model parameters are fixed over time may limit its performance. A common problem in BCI decoding is that neurons are unstable. Micro-movements of the electrode array relative to the brain can cause the amplitude of recorded neurons to change dramatically [5]. Furthermore, there is evidence that neural tuning curves themselves may change over time, slowly altering the relationship between firing rate and intended movement [1], [4], [10]. Traditional Kalman filters will not compensate for this variation.

B. Parameter Tracking Algorithm

To compensate for neural tuning changes, we propose an adaptive decoding model with parameter tracking. In this model, we extract the parameter vector $\boldsymbol{\beta}^{(i)}$ for every neuron i and treat it as a state vector. If we also use a linear dynamical system to model this state vector, then the history of firing rates of neuron i and estimated limb states can be

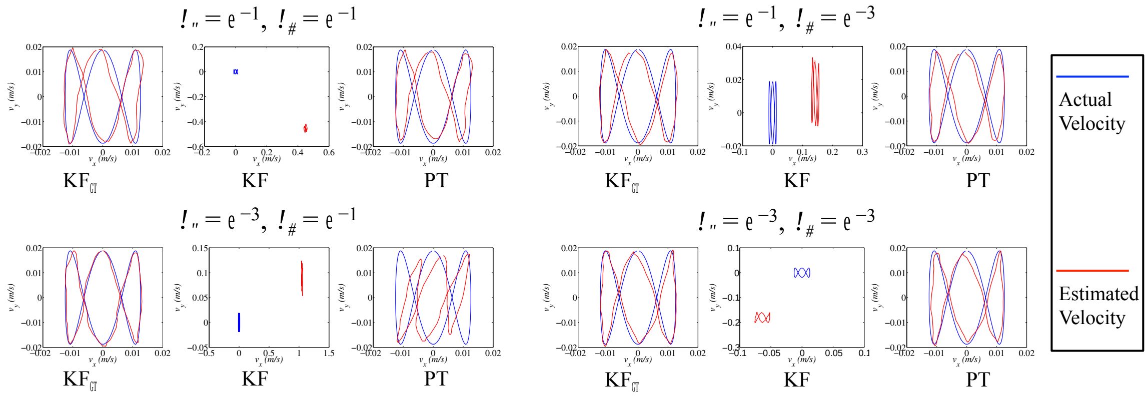

Fig. 2. Simulation results: Reconstructed velocity of the 100,000th trial of the simulation resulting from three of the algorithms under various amounts of observation and parameter noise. Note the static KF (middle panels) tends to show an offset, indicative of strongly biased decoding. In contrast, the stabilized dual Kalman filter (right-hand panels) performs nearly as well as the ground-truth Kalman filter (left-hand panels) under most noise contexts.

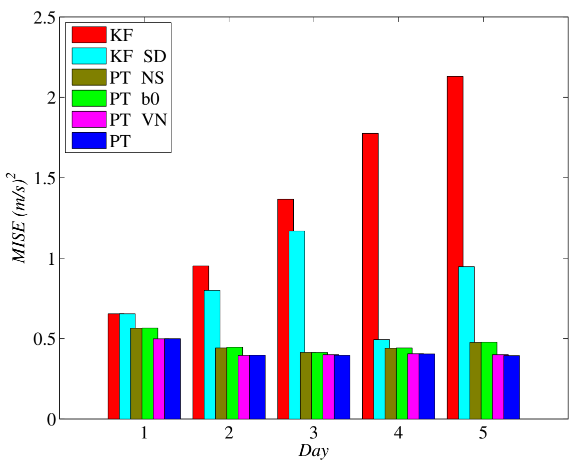

Fig. 3. Off-line trajectory reconstruction results: MISE of different methods on the offline data.

to eliminate the need of calibration, we implement a dual Kalman filter to track both the limb states and the parameters, augmented with two stabilizing heuristics: baseline firing rate estimating and velocity normalization. Our stabilized dual Kalman filter performs well in both simulation and in estimating arm movement trajectories off-line.

Here we focused on the instability of the neural tuning parameters while assuming fixed variance. Testing how much improvement may be gained by also tracking the variance remains the subject of future work. We also assumed that the number of neurons we tracked remained fixed. In practice, neurons may drop out or come in to the recording over time. This complicates the implementation of parameter tracking, because the dimensionality of the tuning matrix will change over time [8]. One way to simply capture this behavior would be to always track a stable “maximum” number of neurons. Those that correspond to blank signals would return tuning coefficients of zero. If the residual variance assigned to those units is constrained to be non-zero, they should not affect the decoding solution. As neurons come in to the recording, the algorithm would start to measure their tuning. Implementation of this extension remains a subject of future work.

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