Adaptive Decoding of Hand Movement Trajectories from Simulated Spike Train Observations from a Dynamic Ensemble of Motor Cortical Neurons

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Abstract:

One of the many challenges in long-term decoding from chronically implanted electrodes involves tracking changes in the firing properties of the neural ensemble while simultaneously reconstructing the desired signal [1]. We offer an approach to dealing with this problem based on adaptive point process filtering. In particular, we construct a lock-step adaptive filter built upon stochastic models for: a) the receptive field parameters of individual neurons within the ensemble, b) the biological signal to be reconstructed, and c) the instantaneous likelihood of firing in each neuron given the current state of a) and b). We assess the ability of this filter to maintain a good representation of movement information in a simulated ensemble of primary motor neurons tuned to hand kinematics.

Summary:

Long-term signals obtained from chronically implanted electrodes are dynamic in that the responses to repeated stimuli or motor commands can change in time. These changes could be due for example to adaptation or plasticity at the level of individual neurons, changes in the firing of unobserved neural inputs, or changes in the population of neurons that are observable to the recording device. In order to address this problem, we simulated a dynamic ensemble of primary motor (MI) neurons responding as they would to control hand movement during a two-dimensional reaching task.

These simulated ensembles contained a population of velocity modulated, cosine-tuned neurons that controlled the hand trajectory, similar to Moran and Schwartz' MI model [2]. Each neuron had static tuning parameters over its lifespan, but was only observable for a limited period of time. After a fixed interval, that neuron became lost to the recording device and was removed from the population, and a previously unobserved neuron with unknown firing properties became observable. We ran a number of simulations, modulating both the total number of neurons observable at one time and the rate of dropout of individual neurons. This simulation scenario presents a challenge to an algorithm trying to reconstruct the hand velocity signal from only the spike train observations in that it must maintain a sufficiently accurate estimate of the hand kinematic variables in order to estimate the firing properties of newly observed neurons, and incorporate those estimated firing properties to improve the kinematic variable estimates.

We have previously constructed an adaptive estimation framework that can be applied to both encoding problems, such as tracking changes in ensemble firing properties, and decoding problems, such as reconstructing an intended motor output form an ensemble of motor neurons. We also presented two approaches to address problems of adaptive decoding, where it is necessary to track changes in the firing properties of the ensemble while simultaneously reconstructing a driving signal. One involves augmenting the state space of our stochastic state point process filter [3] to include both encoding and decoding variables. The second approach, which is more easily applicable to high-dimensional systems, involves running two filters in lock-step, using the estimates derived at each time step from one filter as part of the input into the second, and vice versa.

In order to apply our stochastic state point process filter to this problem, we first constructed a stochastic intensity model for the firing of each neuron:

$$l^i(v_k, q_k^i) = \exp(b_1(t_k) + b_2(t_k) v_x(t_k) + b_3(t_k) v_y(t_k)) .$$

Here, $q_k^i = \begin{bmatrix} b_1(t_k) & b_2(t_k) & b_3(t_k) \end{bmatrix}^T$ is a vector representing the receptive field parameters for the i^{th} neuron at time t_k and $v_k = \begin{bmatrix} v_x(t_k) & v_y(t_k) \end{bmatrix}^T$ is the hand velocity signal at time t_k. Next, we constructed stochastic models for the evolution of both the receptive field parameters of each neuron and the velocity and direction of the hand movement signal:

$$q_k^i = A^i q_{k-1}^i + h_k^i ,$$
$$v_k = F v_{k-1} + e_k ,$$

where $\mathrm{var}[h_k^i] = \mathbf{W}_q^i$ and $\mathrm{var}[e_k] = \mathbf{W}_v$ are the covariances of the stochastic components of the parameter and velocity state vectors at each time step. The pair of filters for estimating the expected value, $q_{k|k}^i$, and variance, $W_{k|k}^i$ of the receptive field parameters and the expected value, $v_{k|k}$, and variance, $V_{k|k}$ of the hand movement velocity can be written as:

$$W_{k|k}^i = \left[[A^i W_{k-1|k-1}^i A^{i\mathbf{T}} + W_q]^{-1} + l^i \left(\frac{\partial \log l^i}{\partial q_k^i} \right)^T \left(\frac{\partial \log l^i}{\partial q_k^i} \right) \Delta t - \left(\frac{\partial^2 \log l^i}{\partial q_k^i \partial q_k^{iT}} \right)^T \left[\Delta N_k^i - l^i \Delta t \right] \right]^{-1},$$

$$q_{k|k}^i = A^i q_{k-1|k-1}^i + W_{k|k}^i \frac{\partial \log l^i}{\partial q_k^i} \left[\Delta N_k^i - l^i \Delta t \right],$$

$$V_{k|k} = \left[[F V_{k-1|k-1} F^{\mathbf{T}} + W_n]^{-1} + \left(\frac{\partial \log l}{\partial v_k} \right)^T Diag[\, l \Delta t\,] \left(\frac{\partial \log l}{\partial v_k} \right) - \sum_{i=1}^{C} \left(\frac{\partial^2 \log l^i}{\partial v_k{}^2} \right)^T \left[\Delta N_k^i - l^i \Delta t \right] \right]^{-1},$$

$$v_{k|k} = F v_{k-1|k-1} + V_{k|k} \frac{\partial \log l}{\partial v_k} \left[\Delta N_k - l \Delta t \right].$$

This adaptive estimation procedure is similar to an extended Kalman filter, except that its inputs are spiking events rather than continuous valued observations.

At the beginning of each simulation, there was a 10 minute period of supervised learning, when the algorithm was provided with the true simulated hand kinematic signal, and only the receptive field parameters of the ensemble needed to be estimated. After this initial period, the simulation switched to an unsupervised scenario, where both the receptive field parameters and the movement signal were simultaneously estimated for up to 24 hours of simulation time. During this period, neurons would drop out of the ensemble at fixed intervals, and be replaced by other neurons with unknown receptive field parameter vectors. When a previously unobserved neuron was detected for the first time, it was initialized with an uninformative receptive field with a minimal background firing rate. The initial variance about its receptive field parameters was set to be large, allowing them to change rapidly, based on the relationship between the neuron's firing pattern and the estimated movement signal from the rest of the ensemble. The newly observed neuron did not contribute to the signal estimate until the determinant of the variance of its parameter estimates dropped below a specified level.

We examined the mean squared error between the true simulated and estimated hand trajectory and its change in time while modulating a) the total number of neurons observable at one time and b) the rate of dropout of individual neurons. For an ensemble with a large number of neurons and a slow rate of neuron dropout, the mean squared error remained constant after the switch to unsupervised learning. When either the total number of neurons in the ensemble at one time was decreased or the rate of dropout was increased, the error would increase initially and asymptote to a new level.

This adaptive filtering framework provides a useful approach for maintaining information about the firing properties of a neural population whose members are constantly changing in an unsupervised scenario. This application will be important for the construction of neural prosthetic devises, where chronically implanted electrodes are used to extract sensory signals or motor commands from dynamic neural ensembles [4-7].

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