Proceedings of the 26th Annual International Conference of the IEEE EMBS
San Francisco, CA, USA • September 1-5, 2004

Reconstruction of Hand Movement Trajectories from a Dynamic Ensemble of Spiking 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 provide an approach to 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 assessed the ability of this filter to maintain a good representation of movement information in a dynamic ensemble of primary motor neurons tuned to hand kinematics. We simulated a recording scenario for this ensemble, where neurons were continuously becoming lost to the recording device while recordings from other, previously unobserved neurons became available. We found that this adaptive decoding algorithm was able to maintain accurate estimates of hand direction, even after the entire neural population had been replaced multiple times, but that the hand velocity signal tended to degrade over long periods.**

Keywords— **Dynamic Estimation, Point Process Models, Neural Motor Prosthetics**

I. INTRODUCTION

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.

This presents a particular problem for the design of neural prosthetic devices that use information from an ensemble of spiking neurons to estimate biological or behavioral signals. This is because the estimation and control algorithms for such a device would need to be able to simultaneously estimate both the appropriate sensory or motor signal and the dynamic components of the firing properties of each cell in the ensemble. For example, a chronically functioning motor prosthetic device using multi-unit activity from motor cortex would need to account for changes in the neural population due to cell death or to neurons becoming lost to the recording device while other, previously unobserved neurons became observable. In order to make use of the information in these new cells, it would first be necessary to estimate their receptive field structure. Whereas this could be accomplished by continually retraining the prosthetic device's estimation and control algorithms, a solution that used the already available estimated movement signal to approximate the receptive field structure of the new cells would be more practical.

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 static decoding problems, such as reconstructing an intended motor output form an ensemble of motor neurons. This current problem could well be described as one of adaptive decoding, where it is necessary to track changes in the firing properties of the ensemble while simultaneously reconstructing a driving signal. In [2], we presented two approaches to address this class of problem. The first involves augmenting the state space of our stochastic state point process filter 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. We showed that the point process framework could successfully be applied to reconstruct a simulated signal in the presence of a dynamic tuning function. Here we bring these methods to bear on a much larger data set comprising spike train data from the arm region of motor cortex, which has been manipulated to simulate a dynamic population of neurons over long time periods.

II. METHODOLOGY

A. Behavioral Task and Neural Recordings

An electrode array was implanted in the motor cortex (MI) of a Macaca mulatta monkey that had been trained to perform a visually-guided hand movement task. The monkey gripped a low-friction manipulandum that controlled the movement of a cursor on a video monitor and traced the movement of a second cursor on the screen. The second cursor followed predefined, randomly generated, two-dimensional trajectories encompassing a wide range of hand velocities and movement directions. The position of the monkey's hand was observed using a digitizing tablet attached to the manipulandum.

The electrode array was implanted a region of MI that had a significant number of neurons whose firing was tuned to arm kinematics. Action potentials were generated by thresholding the waveforms and the resulting spikes were sorted offline. More specific details of the neural recording methodology have been previously published [3-4]. Typical firing rates for these neurons ranged from 5 to 60 Hz.

B. Simulation of Dynamic Ensemble

Simultaneous hand movement data and spike train recordings from each neuron were available for a total of just over 20 minutes, divided into individual trials of approximately 10 seconds each.

In order to extend the total time that the estimation algorithm would be required to reconstruct the behavioral signal, we simulated a chronic recording scenario by concatenating randomly shuffled trials onto the existing data, using the data from each trial multiple times.

Thus we created a simulated recording scenario using real data from primate motor cortex. Fig. 1 depicts the constructed pattern of data acquisition for this simulated recording scenario. For the first 20 minutes of this simulated scenario, shown in figure 1 in red, both the spiking activity of the neurons and the hand kinematic signal were made available, creating a period of supervised learning, where an estimation algorithm could use the hand movement signal to estimate a model for the firing properties of each cell as a function of hand kinematics. During this period, the neural population was static in that the spiking data for each cell was always present.

Immediately after this initial period followed a much longer adaptive decoding period, shown in figure 1 in blue, characterized by a dynamically evolving population of neurons and simultaneous estimation of both the hand movement signal and the tuning properties of newly observed neurons. During this period, no information about the hand kinematics was available, and therefore it needed to be estimated from the spiking activity of the population of neurons and their estimated tuning functions. Additionally, each neuron would only be observable for a limited period of time and then would become lost to the simulated recording device and would have to be removed from the population, while a previously unobserved neuron with unknown firing properties became observable. Since the total number of cells available was limited, in order to simulate these "new" cells, we used the spiking data from the same cells that had just been removed from the ensemble. However, since it was assumed that nothing was known about the firing properties of these newly introduced cells, the estimation algorithm would have no knowledge that the tuning function of this cell was the same as the one that was dropped, and would therefore have to estimate it anew in order to be able use the neuron's spiking activity to maintain the movement signal estimate.

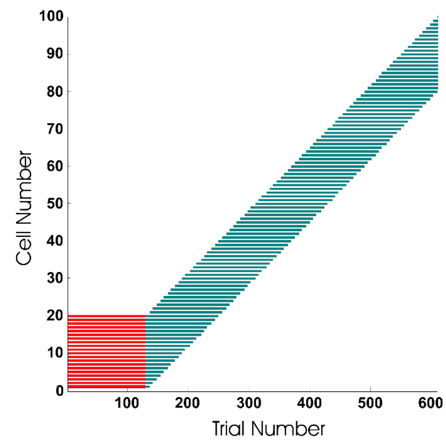

Fig. 1. Simulated recording scenario, illustrating times when each cell in the dynamic ensemble is active. Red lines indicate the initial period of supervised learning. Blue lines indicate the subsequent period of adaptive decoding.

C. Dynamic Estimation Algorithm

We modeled the receptive field of each neuron in the ensemble as a velocity modulated, cosine tuning function responding to the hand movement signal, similar to Moran and Schwartz' model of primary motor neuron receptive fields [5]. Under the point process intensity model for neural spiking discussed in [2,6], this corresponds to a conditional intensity function of:

$$\begin{aligned}\lambda^i(v_{k,}\theta_k^i) &= \exp(\alpha_1(t_k)+\alpha_2(t_k)v(t_k)\cos(\theta(t_k)-\theta_p(t_k)) \\ &= \exp(\beta_1(t_k)+\beta_2(t_k)v_x(t_k)+\beta_3(t_k)v_y(t_k))\end{aligned}.$$

Here, θ_p is the preferred direction of the neuron, and $v_x(t_k)$ and $v_y(t_k)$ are the velocities in the x and y directions respectively. $\theta_k^i = \left[\beta_1(t_k) \quad \beta_2(t_k) \quad \beta_3(t_k)\right]^T$ is a vector representing the receptive field parameters for the i^{th} neuron at time t_k and $v_k = \left[v_x(t_k) \quad v_y(t_k)\right]^T$ 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 of the hand movement signal:

$$\theta_k^i = A^i\theta_{k-1}^i + \eta_k^i,$$

$$v_k = Fv_{k-1} + \varepsilon_k,$$

where A^i and F are state transition matrices for each neurons' tuning parameters and the hand velocity signal respectively, and $\mathrm{var}[\eta_k^i] = \mathbf{W}_\theta^i$ and $\mathrm{var}[\varepsilon_k] = \mathbf{W}_v$ are the covariances of the stochastic components of the parameter and velocity state vectors at each time step.

Using these stochastic models we constructed two distinct point process filters that ran simultaneously in lock step with one another. The form of these filters is described in detail in [2]. During the initial 20-minute period of supervised learning, the algorithm was provided with the true hand trajectory and estimated only the receptive field parameters of each cell in the ensemble. 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 simulated recording time. During this period neurons would drop out at a rate of approximately one per minute, and would be removed from the estimated ensemble.

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.

III. Results

We compared the estimated tuning functions for each neuron immediately following the initial training period to those estimated after 2 hours of adaptive decoding. Fig. 2 illustrates the tuning functions for 20 neurons graphically. Under this cosine tuning model, each cell has a preferred direction where, for any fixed movement velocity, the firing intensity is maximal. The intensity is additionally linearly modulated by the hand speed. The ensembles depicted in the two panels contain identical neurons being estimated after training (Fig. 2A) and after extended adaptive decoding (Fig 2B).

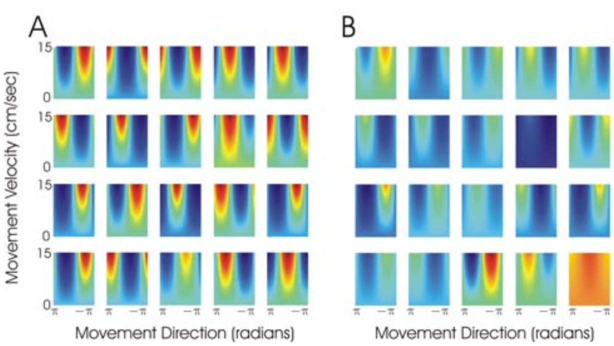

Fig. 2. Estimated tuning functions for 20 neurons in the ensemble (A) immediately after supervised learning and (B) after 2 hours of adaptive decoding.

The estimated preferred directions for each neuron in the ensemble in Fig. 2B are virtually identical to those from the recently trained receptive fields in Fig 2A. However, the degree of velocity modulation in the adaptively decoded ensemble decreased for most of the neurons.

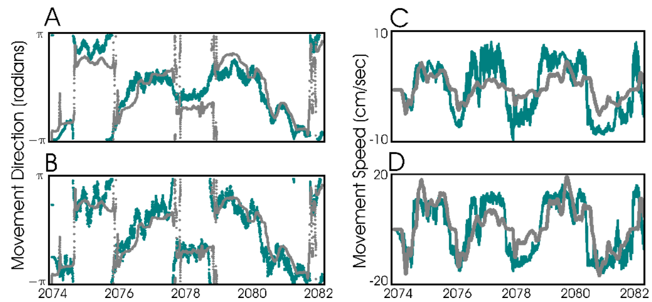

Fig. 3. Hand trajectory direction and velocity trajectory (gray) and reconstruction (cyan). (A, C) represent movement and direction reconstruction respectively after 2 hours of adaptive decoding. For comparison, (B, D) are reconstructions immediately following supervised learning.

Fig. 3 shows an example of hand trajectory reconstruction for a single trial, again immediately after training and after adaptive decoding. The gray lines represent the true hand trajectory and the cyan lines are the estimates. The quality of reconstruction for movement direction is similar at the end of the simulation to its initial levels. The hand speed reconstruction is initially accurate, and after an extended period of decoding still follows the trends of the true hand movement, but the magnitude of these estimates tend to be scaled versions of the true trajectories.

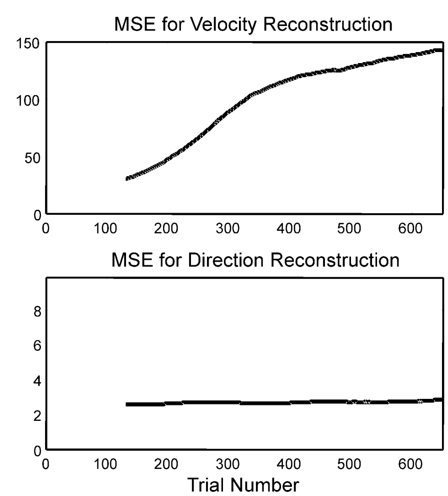

Fig. 4. Average mean squared error for velocity and direction reconstruction.

This trend is further demonstrated in Fig. 4, which plots the average mean squared error between the true hand trajectory velocity and direction and the reconstruction estimates. The error level for the velocity reconstruction begins to degrade immediately after the training session ends and neurons begin to drop out of the ensemble. It continues to degrade and eventually begins to plateau to a new level. The mean squared error for the hand movement direction, on the other hand, does not degrade upon switching to the adaptive decoding scenario and remains stable even after the entire neural population has been replaced numerous times.

IV. DISCUSSION

The challenge presented in this adaptive decoding problem is to 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 its hand movement reconstructions. Each time a neuron drops out of the ensemble, the signal reconstruction accuracy could decrease. When a "new" neuron then becomes observable, the question becomes whether it is possible to estimate its tuning function from this degraded hand movement estimate sufficiently well, so that this new neuron becomes as informative about the hand signal as the one that was lost.

Here we solved this problem by constructing stochastic state evolution models for the receptive field parameters of each neuron in the ensemble, as well as for the motor output signal, and using a point process intensity model for the spike train observation data. Using these stochastic models, we constructed two stochastic state point process filters that estimated the posterior probability distributions of both the motor signal and the neural tuning parameters. These filters are point process analogues of the Kalman filter, using as their inputs spiking events rather than continuous valued observations.

Since we repeatedly use the same real neurons to create the simulated ensemble in this example, the two sets of tuning functions plotted in Fig 2 should be similar if the adaptive decoding algorithm is successfully estimating the receptive field structure of new neurons. The fact the preferred directions are virtually identical throughout the adaptive decoding scenario indicates that this information is maintained robustly in the evolving ensemble. This finding is reinforced by the stability of the reconstruction accuracy for movement direction as evidenced by its flat average mean squared error. Conversely, the speed modulation parameter tends to scale down during adaptive decoding, causing a washout effect, which makes future tuning function estimation even more difficult. This sets up a cycle that causes the overall representation of the speed component of the signal to degrade. This continues until the reconstruction accuracy reaches a new asymptotic level.

V. CONCLUSION

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 [7-10].

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