Adaptive Neural Filtering Applied to Hand Movement Coding in Primate Primary Motor Cortex During a Hand Tracking Task

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We have previously developed a general statistical paradigm for analyzing neural signals from spike-train observations [5]. In past work we have shown how this paradigm can be used to analyze and evaluate neural receptive field models [1,3]. We have also shown how this paradigm can be used to decode external variables from ensemble firing patterns using a two-stage approach [2]. Here, we bring these tools to bear on the problem of hand movement coding in primate motor cortex.

Theory:

The starting point for this paradigm comes from treating neural firing as a stochastic process and thereby relating the receptive field model for a neuron to the probability of it firing a spike at each point in time. Any stochastic point process representing neural spike data can be characterized by a conditional intensity function, $l(t \mid x_t, H_t)$, where x_t represents the vector of all state variables and parameters specifying the receptive field model for the neuron, and H_t represents the history of all spiking activity up until time t. The value $l(t \mid x_t, H_t)\Delta t$ then approximates the probability of a spike occurring in the interval $[t, t+\Delta t]$.

Under a two-stage decoding framework, the first, or encoding stage involves characterizing the function $l(t \mid x_t, H_t)$. By adopting this probabilistic framework we immediately get the benefit of well-established measures of model goodness-of-fit, such as the Kolmogorov-Smirnov statistic. These measures can be used to compare the relative quality of competing models or to analyze individual models independent of one another.

The second, or decoding stage works by tracking the evolution of the probability density associated with an evolving set of external state parameters. In general, we are interested in $p(x_k \mid N_{0:k})$, where x_k is a state vector describing some external stimulus at time k and $\{N_{0:k} : 0 \le t \le k\}$ is the spike train up to and including time k. We can find a recursive expression for this distribution by applying Bayes' rule and using the Chapman-Kolmogorov equation to describe the probabilistic evolution of the receptive field.

$$p(x_k \mid \mathbf{N}_{1:k}) = \frac{p(\mathbf{N}_k \mid \mathbf{N}_{1:k-1}, x_k)}{p(\mathbf{N}_k \mid \mathbf{N}_{1:k-1})} \int p(x_k \mid x_{k-1}) p(x_{k-1} \mid \mathbf{N}_{1:k-1}) dx_{k-1} \tag{1.1}$$

This equation is the basis for all of our recursive estimation algorithms.

By applying efficient Gaussian approximations, we can solve this expression analytically to obtain a recursive algorithm for the instantaneous a posteriori estimate:

$$x_k = F x_{k-1} + v_k \tag{1.2}$$

$$\mathbf{W}_{k|k} = \left[[\mathbf{F} \mathbf{W}_{k-1|k-1} \mathbf{F}^{\mathrm{T}} + \mathbf{W}_{\mathrm{v}}]^{-1} + \left[\frac{\partial \log l}{\partial x_k}\right]^T Diag[l\Delta t] \left[\frac{\partial \log l}{\partial x_k}\right] - \left[\frac{\partial^2 \log l}{\partial x_k{}^2}\right]^T \left[N_k - l\Delta t\right] \right]^{-1} \tag{1.3}$$

$$x_{k|k} = \mathbf{F} x_{k-1|k-1} + \mathbf{W}_{k|k} \frac{\partial \log l}{\partial x_k} \left[N_k - l\Delta t\right] \tag{1.4}$$

where **F** is a matrix describing the expected evolution of the state variables , v_k is a white noise process with a covariance matrix given by $\mathbf{W}_{\mathrm{v}}$. This adaptive estimation procedure is similar to an extended Kalman filter, except that its inputs are sequences of all-or-nothing events rather than continuous valued observations.

Evaluating receptive fields and hand movement tracking from primate MI neurons:

In collaboration with Wilson Truccolo, and Professor Donoghue's group at Brown University, we have analyzed the firing of 195 MI neurons as a monkey performed a hand-based movement task. The Macaca mulatta monkey was trained to grip a low-friction manipulandum that controlled the movement of a cursor on a video monitor, and follow the movement of a second cursor on the screen. The second cursor traced out predefined, randomly generated, two-dimensional trajectories encompassing a wide range of velocities and movement directions.

We fit the cortical spiking data from this experiment to a static cosine-tuning type model of hand velocity and direction [4] using maximum likelihood techniques. This model provided a conditional firing intensity for each point in time as the animal performed the movement task. We measured the goodness of fit between the firing and the model using both the r-squared values from a GLM fit, and using the Kolmogorov-Smirnov statistic. We find that for a specific model specification, the maximum likelihood coefficients all have significant p-values, yet most of the cells fire spike trains that do not fit within the 99% confidence intervals for the KS test.

We also fit a hand-position tuned receptive field model to these same neurons, again using maximum likelihood based methods and compared the goodness-of-fit for each neuron to both models. We found that some neurons were better tuned to position, and others better tuned to velocity and direction.

The preliminary results from these investigations suggest that most of these cells have some significant tuning either to velocity and direction or to hand position variables. However, as expected, the Kolmogorov-Smirnov test results show that the neither model can completely capture the firing properties of any of these neurons. This could be due to the omission of other important firing related variables, an imperfect specification of the model intensity function as a function of those variables, an incorrect model of the stochasticity of firing based on this intensity model, or any combination of these.

We have also applied the point-process adaptive decoding algorithm described above, both as another measure of the goodness of fit of the model to the data, and in order to compare this algorithm to other established decoding techniques such as linear regression. We find that we are able to track both velocity and direction of movement much more reliably with a point-process analogue of the extended Kalman filter, than with linear regression methods. However, with this preliminary firing model, the absolute estimation error is still large when integrated to get hand position estimates.

These preliminary results have highlighted the applicability of our point-process filters to analyzing motor system problems and demonstrated an advantage of approximate Baysian methods over traditional encoding and decoding methods. These techniques will allow better characterization of motor neuron firing properties and better reconstruction of the desired motor output signal that these neurons contain, both potentially vital components in the potential development of neural motor prostheses [6].

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