MODEL COMPARISON IN AVIAN AUDITORY SYSTEM

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INTRODUCTION

We have stimuli and response data from ~600 neurons in MLd (midbrain), OV (thalamus), and higher regions (field L, CM), and wish to find optimal models for their stimulus-response functions. We approach this problem in two ways. First, we systematically find optimal preprocessing models for the stimuli, and second, fit the stimulus-response function using a variety of models. We compare the optimal preprocessing and models for two classes of auditory stimuli, conspecific birdsong and modulation-limited noise.

GENERALIZED GAIN CONTROL

Previous work has shown preprocessing sound with Lyon's cochlear model with adaptive gain control improves the linear fit to stimulus-response data (Gill et. al 2006). In addition, representing stimuli in terms of their history-conditioned probabilities (surprise) improves predictions in higher regions (Gill et. al 2008). In the visual system, models of gain control involving variance have been shown to predict adaptive effects (Wark et. al 2009). Here we generalize the concept of adaptive gain control, providing a framework to uniformly test these types of effects. We define the "optimal" gain control for a given neuron as the one that produces the best linear fit between the preprocessed stimulus and response.

We model gain control effects as a function of the log-spectrogram. Let $s(\omega,t)$ be a single spectrogram entry at frequency ω and time t. In a simple functional model, each frequency band of the spectrogram is associated with gain control element whose kth output is given by $r_k(t)$. First we define several types of gain:

- Running-mean: $G^k_{\hat{\mu}}(t) = \hat{\mu}_k(t)$
- Running-variance: $G^k_{\hat{\sigma}}(t) = (\hat{\sigma}_k(t))^{-1}$
- Nearest Neighbor: $G^k_{NN}(t) = \frac{1}{\tau N}\sum_{i=1}^{N} \lambda_{ik} r_i(t-1)$
- Surprise: $G^k_S(t) = log(P[s(k,t)|s(k,\tau < t)])^{-1}$

Gain control can be subtractive or divisive. In regards to the simple functional model, we test the following different types:

- Mean-subtracted: $r_k(t) = s(k,t) - G^k_{\hat{\mu}}(t)$
- Variance-normalized: $r_k(t) = s(k,t)\, G^k_{\hat{\sigma}}(t)$

- Divisive Coupled Feedback: $r_k(t) = s(k,t)\,(G^k_{NN}(t))^{-1}$
- Subtractive Coupled Feedback: $r_k(t) = s(k,t) - G^k_{NN}(t)$
- Divisive Surprise: $r_k(t) = s(k,t)\,G^k_S(t)$

We can also apply the same concepts of gain to Linear-nonlinear Poisson and integrate-and-fire models.

OPTIMAL NONLINEARITIES

Let $\mathbf{s} : \mathbb{R} \to \mathbb{R}^M, \mathbf{s}(t)$ be a time-varying stimulus with M channels, $\mathbf{s}_t \in \mathbb{R}^{PM}$ the row-vector representing multi-channel stimulus history with P delays at time t, and $r(t)$ the PSTH in response to $\mathbf{s}(t)$. A STRF is a row vector $\mathbf{a} \in \mathbb{R}^{PM}$ multiplied with $\mathbf{s}_t$ to produce a model response. Using techniques such as spike-triggered covariance, we can create a family of D STRFs $\{\mathbf{a}_i\}$ that produce multi-dimensional output $\{x_i \in \mathbb{R}\}$, where $x_i = \mathbf{a}_i^T \mathbf{s}_t$. The generalized model we consider here is given as:

$$\hat{r}(t) = f(x_1, ..., x_D)$$

where $f : \mathbb{R}^D \to \mathbb{R}$ is an arbitrary nonlinear output function.

Radial Basis Function Fit to Output Nonlinearity. We expect from this study that the form of the output nonlinearity f will differ depending on cell type, region, and stimulus class. Therefore we require a non-parametric, potentially multi-dimensional set of nonlinear basis functions to fit f. We can use a linear combination of radial basis functions to do this:

$$f(\mathbf{x} \in \mathbb{R}^D) \approx \sum_{i=1}^{B} b_i \phi(\|\mathbf{x} - \mathbf{c}_i\|)$$

where $\mathbf{c}_i$ is the center of each basis function. We set $\mathbf{b} = [b_1 \cdots b_B]$ as the vector of basis coordinates.

We fit the STRF weights $A = [\mathbf{a}_1 \cdots \mathbf{a}_D]$ and output nonlinearity coordinates $\mathbf{b}$ with a staggard optimization procedure:

(1) Generate an initial guess A_0 by fitting with linear optimization, spike-triggered covariance, or MID.
(2) Construct a histogram of linear responses to define the domain of f and use it to determine the number of basis functions B and center points $\{c_i\}$.
(3) Fit f using linear optimization procedures while holding A_0 fixed, minimizing the sum-of-squares error between $\hat{r}(t)$ and $r(t)$.
(4) Fit f^{-1}, the inverse of f, using another set of radial basis functions.

(5) Use f^{-1} to invert $r(t)$, producing an inverted response $r^{-1}(t)$, and refit A by minimizing sum-of-squares error with the inverted response.
(6) Repeat steps 2-5 until both A and $\mathbf{b}$ have converged.

References

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