Coding and computation by neural ensembles in the primate retina

Liam Paninski

Department of Statistics and Center for Theoretical Neuroscience
Columbia University
http://www.stat.columbia.edu/~liam
liam@stat.columbia.edu
June 7, 2010

co-PI’s: E. Simoncelli (NYU), E.J. Chichilnisky (Salk)
— with J. Pillow (UT Austin), G. Field, J. Gauthier, J. Shlens (Salk), A. Litke (UCSC),
E. Lalor (TC Dublin), S. Koyama (CMU), Y. Ahmadian, J. Kulkarni, H. Liu, T.
Retinal ganglion neuronal data

Preparation: dissociated macaque retina
— extracellularly-recorded responses of populations of RGCs

Stimulus: random spatiotemporal visual stimuli (Pillow et al., 2008)
Receptive fields tile visual space
Multineuronal point-process model

\[ \lambda_i(t) = f \left( b_i + \tilde{k}_i \cdot \bar{x}(t) + \sum_{i',j} h_{i',j} n_{i'}(t - j) \right), \]

— likelihood is easy to compute and to maximize (concave optimization) (Paninski, 2004; Paninski et al., 2007; Pillow et al., 2008)
— close connections to noisy integrate-and-fire model
Optimal Bayesian decoding

\[ E(\vec{x}|\text{spikes}) \approx \arg \max_{\vec{x}} \log P(\vec{x}|\text{spikes}) = \arg \max_{\vec{x}} [\log P(\text{spikes}|\vec{x}) + \log P(\vec{x})] \]

— Computational points:

- \( \log P(\text{spikes}|\vec{x}) \) is concave in \( \vec{x} \): concave optimization again.

- Decoding can be done in linear time via standard Newton-Raphson methods, since Hessian of \( \log P(\vec{x}|\text{spikes}) \) w.r.t. \( \vec{x} \) is banded (Pillow et al., 2010; Ahmadian et al., 2010).
Optimal Bayesian decoding

\[ E(\vec{x} | \text{spikes}) \approx \arg \max_{\vec{x}} \log P(\vec{x} | \text{spikes}) = \arg \max_{\vec{x}} [ \log P(\text{spikes} | \vec{x}) + \log P(\vec{x}) ] \]

— Computational points:
- \( \log P(\text{spikes} | \vec{x}) \) is concave in \( \vec{x} \): concave optimization again.
- Decoding can be done in linear time via standard Newton-Raphson methods, since Hessian of \( \log P(\vec{x} | \text{spikes}) \) w.r.t. \( \vec{x} \) is banded (Pillow et al., 2010; Ahmadian et al., 2010).

— Biological point: paying attention to correlations improves decoding accuracy.
Application: how important is timing?

— further applications: decoding velocity signals (Lalor et al., 2009), tracking images perturbed by eye jitter (Pfau et al., 2009)
Next steps: reconsidering the model

\[ \lambda_i(t) = \exp \left( k_i \cdot x(t) + h_i \cdot y_i(t) + \sum_{i \neq j} l_{i,j} \cdot y_j(t) \right) \]

**Pros:**
- Tractable model-fitting and optimal decoding
- Captures response statistics

**Cons:**
- Instantaneous coupling filters
- No explicit Common Input
Considering common input effects

— universal problem in network analysis: can’t observe all neurons!
Intracellular findings:

- RGCs receive strongly correlated synaptic input in the absence of modulated light stimuli

- ON RGCs are weakly electrically coupled

- No electrical coupling seen between OFF RGCs
Extension: including common input effects

\[ \lambda_i(t) = \exp \left( k_i \cdot x(t) + h_i \cdot y_i(t) + \sum_{i \neq j} l_{i,j} \cdot y_j(t) + Lq(t) \right) \]
Direct state-space optimization methods

To fit parameters, optimize approximate marginal likelihood:

$$
\log p(\text{spikes}|\theta) = \log \int p(Q|\theta)p(\text{spikes}|\theta, Q)dQ \\
\approx \log p(\hat{Q}_{\theta}|\theta) + \log p(\text{spikes}|\hat{Q}_{\theta}) - \frac{1}{2} \log |J_{\hat{Q}_{\theta}}| \\
\hat{Q}_{\theta} = \arg \max_{Q} \left\{ \log p(Q|\theta) + \log p(\text{spikes}|Q) \right\}
$$

— $Q$ is a very high-dimensional latent (unobserved) “common input” term. Taken to be a Gaussian process here with autocorrelation time $\approx 5$ ms (Khuc-Trong and Rieke, 2008).

— correlation strength specified by one parameter per cell pair.

— all terms can be computed in $O(T)$ via banded matrix methods (Paninski et al., 2010).
Inferred common input effects are strong

— note that inferred direct coupling effects are now relatively small.
Common-input-only model captures x-corrs

— single and triple-cell activities captured well, too (Vidne et al., 2009)
Decoding the stimulus and hidden input

\[
\arg \max_{\vec{x}} p(\vec{x} | y, \theta) = \arg \max_{\vec{x}} \int p(\vec{x}, Q | y, \theta) dQ \approx \arg \max_{\vec{x}, Q} p(\vec{x}, Q | y, \theta)
\]
Models lead to similar decoding performance

...but CI model is more robust to spike jitter and deletions (Vidne et al., 2009).
Next steps: inferring cones

— cone locations and color identity can be inferred accurately with high spatial-resolution stimuli via maximum a posteriori estimates (Field et al., 2010).
Next steps: inferring circuitry?
References


