Optimality in neural adaptation

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Encoding signals in context
Signals occur in a time-varying statistical context

Multiple codes:

• Different components of the stimulus are encoded at different timescales with different coding strategies

• Fluctuations and context (phase and envelope) are encoded separately

Optimal neural coding

• Information maximization in dynamic response properties

• From system to single neuron

• The biophysics of efficient coding
Neural encoding model

Optimal coding hypothesis

• Sensory systems attempt to maximize information transmission

• Should maximize efficient use of available response bandwidth
Dynamically optimal coding

Normalized stimulus representation in the fly visual system

For fly neuron H1, determine the input/output relations throughout the stimulus presentation

Normalized stimulus representation in rat barrel cortex

Extracellular *in vivo* recordings of responses to whisker motion in rat S1 barrel cortex in the anesthetized rat


Normalized stimulus representation in monkey V1

Consistent response functions across stimulus distributions and neuronal population

Ringach and Malone (2007)
What produces this normalized representation?

Normalized input representation in single cortical neurons

R. Mease, A. Fairhall and W. Moody, submitted
Quantifying scaling

The input/output function is, from Bayes’ rule:

\[ P(\text{spike} | \text{stimulus}) = \frac{P(\text{stimulus} | \text{spike}) P(\text{spike})}{P(\text{stimulus})} \]

Replace stimulus \( s(t) \) with scalar value \( s_1 \)

\[ P(s | \text{spike}) \]

\[ P(s) \]

\[ s \]

Distance measure: \( D_{KL}(P_1(s/\sigma | \text{spike}) | P_2(s/\sigma | \text{spike})) \)

\[ P_1(s | \text{spike}) \]

\[ P_2(s | \text{spike}) \]

\[ s \]

\[ s/\sigma \]
This normalized representation emerges in development

At P7, the population exhibits a common threshold function
At P0, threshold functions are variable

This normalized representation emerges in development
This normalized representation emerges in development

Is it activity-dependent?
What needs to be true for this to happen?

Activity-dependent?
Coincidence or cause?

Somatic model parameters leading to gain scaling

\[ C \frac{dV}{dt} = I(t) - g_K n^4 (V - V_K) - g_{Na} m^3 h (V - V_{Na}) - g_l (V - V_l) \]

\[
\begin{align*}
  \frac{dn}{dt} &= \alpha_n(V)(1 - n) - \beta_n(V)n \\
  \frac{dm}{dt} &= \alpha_m(V)(1 - m) - \beta_m(V)m \\
  \frac{dh}{dt} &= \alpha_h(V)(1 - h) - \beta_h(V)h
\end{align*}
\]
Model parameters leading to gain scaling

\[ \frac{G_K}{G_{Na}} = 0.5 \]
\[ \frac{G_K}{G_{Na}} = 1.5 \]

Model parameters leading to gain scaling

Gain increase (\(\sigma_1\) to \(\sigma_2\))
Gain scaling in single cortical neurons

- *Single neurons* exhibit stimulus normalization and thus can act as efficient encoders
- This property appears to emerge in cortical neurons over development
- Modeling shows that the nonlinearity of Na\(^+\) and K\(^+\) channels is sufficient to generate this behavior

Encoding natural signals

- Track stimulus statistics
- .. in order to best encode fluctuations
- *Encode the envelope*
Adapting firing rate encodes the envelope

![Graph with time (s) on the x-axis and rate (spikes/s) on the y-axis showing a response to a stimulus.]

Adaptation assumes estimation

Appropriate adaptation requires an estimation of the input statistics

There are costs to

- adapting too fast
- adapting too slowly

*Speed/accuracy tradeoff*

Is there an **optimal timescale for estimation** that determines timescales of adaptation?
How long does it take to adapt to a new stimulus condition?

Timescales of contrast adaptation in mouse RGC inputs

Wark, Fairhall and Rieke, Neuron (2009)
Multiple timescales of adaptation in RGC inputs

Variance (contrast) adaptation
Mean (luminance) adaptation

How long *should* it take to adapt to a new stimulus condition?
Noise level affects estimation time

SNR ~ 1

SNR ~ 16

Correlation time of luminance affects estimation time
Noise correlation time affects estimation time

Short correlation $\tau_n$

Long correlation $\tau_n$

Finding the optimal luminance adaptation strategy

$s(t) = \mu(t) + \eta(t)$

$\gamma(t)$

$\mu(t)$

$\hat{\mu}(t) = \int d\tau \gamma(\tau)s(t - \tau)$
Predicted adaptation timescale

\[ \tau_{\text{adapt}} = \sqrt{\frac{\beta^2 \tau^2 + \tau^2_{\mu}}{\beta^2 + 1}} \]

\[ \beta = \frac{\sigma_\mu}{\sigma_\eta} \]

Mouse retina is a nearly optimal adaptive encoder
Filter predicts effect of noise on adaptation timescale

Finding the optimal variance adaptation strategy

\[ s(t) = \sigma(t) \eta(t) + \xi(t) \]
Predicted timescale of variance adaptation

\[ \gamma(t) \propto e^{-\frac{2t}{\tau_{\sigma}}} \]

\[ \tau_{\text{adapt}} = \frac{\tau_{\sigma}}{2} \]

RGCs are nearly optimal estimators of stimulus variance

\[ \gamma(t) \propto e^{-\frac{2t}{\tau_{\sigma}}} \]

\[ \tau_{\text{adapt}} = \frac{\tau_{\sigma}}{2} \]
Depends only on stimulus, not system properties

Optimal timescales of adaptation

- The history dependence of adaptation can be accounted for by estimation models

- The rate of optimal variance adaptation may depend only on the correlation time of the variance envelope: the dynamics of variance adaptation may be conserved across systems and species.

- Under the conditions tested, mouse retina and rat cortex may be nearly optimal adaptive encoders

- Biophysical implementation: circuit, synaptic, membrane properties
Optimality through adaptive coding

- Different adaptive processes on different timescales help encode different temporal components of the signal
- Optimality provides a useful framework for interpreting and analyzing the phenomenology of adaptive neural coding

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