Perceptual rivalry as a window into cognition

IPAM: Computational Psychiatry

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Challenges for objective clinical psychiatry

Major historical challenge for psychiatry
- What is the state space?

Major challenges for biological modeling of psychiatry
- What biological scale?
- What are the important non-linearities?

Microscopic (molecular):
genes, ion channels, synapses, …

Macroscopic:
social and language dysfunction, altered perception, information processing, and behavioral outcomes
Psychophysics + electrophysiology is useful for making this tractable.
My starting point 2007

DSM ??

cognitive differences – executive dysfunction, weak central coherence

underconnectivity, EL-imbalance, minicolumn abnormalities, channelopathies, ...

Zimmerman*, Minshew, Ozonoff, Frith, Casanova, others
partnered with Carson C Chow (Laboratory of Biological Modeling, NIDDK, NIH)

working memory differences in autism with minicolumn differences (bridging channel and histological findings with behavior)


→ rivalry modeling

→ general framework for simple cognitive traits
Binocular (static) Rivalry
Changes in perception independent of the stimulus.
Sir Charles Wheatstone 1838 - invents the **stereoscope**, and observes stereoscopic (3D) illusion
Sir Charles Wheatstone 1838 - invents the **stereoscope**, and observes stereoscopic (3D) illusion and **binocular rivalry**.
Levelt’s propositions - stereotypical and non-obvious changes in percept dynamics with change in stimulus

“signal-to-noise” contrast response function

- high, high
- low, low
- high, low
Levelt’s 4th proposition

Percept duration

Levelt, 1965
Binocular rivalry - phenomena

Levitt’s 2nd proposition

![Graph showing percept duration for monkey and human contrast of variable-contrast grating.](Leopold and Logothetis, 1996)
History

- Challenge for mutual inhibition models for many decades (1960s to 2002)
- Laing and Chow (2002) explain how a physiological neuronal model based on a general cortical architecture can explain this (rediscovery and expansion of point in Arrington thesis with Grossberg, 1993)
Binocular Rivalry model - electrophysiology

Stimulus (object) - sensitive populations act like neurons (Wilson and Cowan, 1973) - 1960s-90s Mountcastle, Hubel, Weisel, Albright, Tanaka (MT, IT, etc.)

Pool at different descriptive scales
Binocular Rivalry model- electrophysiology

Pools are also correlated with perception, not just stimuli.

**Leopold and Logothetis 1990s** -
Binocular rivalry neuronal spiking correlated with perception in higher processing areas

(Also evidence from memory experiments by Funahashi, Goldman-Rakic, Colby, others.)
Binocular rivalry presentation

Dynamic — match perceptual dynamics

Static — match stimulus dynamics

Stimulus
Binocular Rivalry model - electrophysiology

\[ C \frac{dV}{dt} = I_{\text{ext}} - I_{\text{mem}}(V, n, h) - I_{\text{AHP}}(V, [Ca]) - I_{\text{syn}} \]

\[ I_{\text{mem}} = g_L(V - V_L) + g_K n^4 (V - V_K) + g_{Na} m^3 h (V - V_{Na}) \]

\[ I_{\text{AHP}} = g_{AHP} [Ca]/([Ca] + 1) (V - V_K) \]

\[ g(x) \]

neuron response function (FI-curve)

\[ \tau_u \dot{u}_i = -u_i + g(S - \beta u_j - \gamma a_i) \]

\[ \tau_a \dot{a}_i = -a_i + u_i \]

where \( \tau_a \gg \tau_u \)

\[ g(x) = \max(0, x)^\eta \]

Leopold and Logothetis, 1996
Binocular Rivalry model with channel kinetics

\[
C \frac{dV}{dt} = I_{\text{ext}} - I_{\text{mem}}(V, n, h) - I_{\text{AHP}}(V, [Ca]) - I_{\text{syn}}
\]
\[
I_{\text{mem}} = g_L(V - V_L) + g_K n^4(V - V_K) + g_Na m^3 h(V - V_{Na})
\]
\[
I_{\text{AHP}} = g_{AHP}[Ca]/([Ca] + 1)(V - V_K)
\]

Laing and Chow, 2002

Type 2 alternations

Levelt's 2nd
Binocular Rivalry model - mechanisms

Stimulus drive
50:50
A:B

Slow fatigue
Release vs Escape

- $S - \gamma a(t)$
  - dominant percept
  - super threshold

- $S - \beta u(t)_{dominant} - \gamma a(t)$
  - suppressed percept
  - subthreshold

- $release^*$ (classic idea)
- escape

* shape of activation function strongly governs which predominates
Escape reproduces Levelt’s propositions.

\[ S = \beta u(t)_{\text{dominant}} - \gamma a(t) \]
Binocular Rivalry model

- Variants - synaptic depression, complex architecture (eye effects, object disparity, etc.)
- General model used to explain alternative forced choice, normalization, flanker-suppressor, and short-term memory.

...and associated cryptic electrophysiology.
Short-term memory revisited: intermittent rivalry
Delay-period activity during memory tasks

ODR task

ITI (4 sec)

Fixation (1 sec)

Cue (0.5 sec)

Delay (3 sec)

Response (0.4 sec)

Reward

Funahashi, Bruce, and Goldman-Rakic 1989

Colby, Duhamel, and Goldberg 1996
Debated - delay activity often highly variable and close to baseline

Miller 2000

Shafi et. al, 2007

Desimone, Duncan (object memory)
SHORT-TERM MEMORY - PHENOMENA

stimulus

perception

ON

OFF

ON

time
Many forms of rivalry have memory

Leopold, et. al 2002
Percept (memory) is more stable with longer delays.

Leopold, et. al 2002

Quartet illusion captures these phenomena plus more.
Drive occurs at the frame transition.
Intermittent rivalry and habituation in the quartet - phenomena

Quartet illusion captures these phenomena plus more.

Vattikuti et. al 2016

Increase duration with increased delay

Acceleration of alternations with fixed delay

number of pings until switch

interval between pings (msec)
Phenomenological constraints

- delay period activity - variable amplitude
- increased percept stability with increased delay
- habituation with fixed parameters
Challenge for the standard rivalry model

- longtime variable in rivalry is fatigue → “anti-memory”
Solutions?

- positive feedback within pool - issue rhythmogenesis and amplitude
- add another positive variable like facilitation, subthreshold current - more complications but plausible
- ...

Intermittent Rivalry and Habituation - Model
Our solution:
→ “topological memory”
standard static rivalry model can do it if:
mutual inhibition + threshold-concave activation
Drive memory with arbitrarily close to zero fixed drive.
Drive memory with **zero-mean noise** only.
Topological memory
zero-mean noise stabilized memory
(no memory without noise)

increased percept stability

Reduced models

Hodgkin-Huxley neurons

increased delay-period
Mechanism notes

- Activity $u$ fixed point competes with fatigue variable.
- Low activity during off-state “stops” buildup of fatigue and stabilizes prior state.
- Mechanism is release, mutual inhibition strength does not factor into percept duration.
- Fatigue variable explains why stability is increased with bigger breaks and scales nonlinearly; slower build up.
- Complex relationship between noise, off-state activity, and fatigue.

Open analysis problems
Acceleration (habituation) is explained by release due to local fatigue such as spike frequency adaptation or synaptic depression in the dominant percept pool.
• Static and intermittent rivalry explained by same simple mutual inhibition type models.

• Threshold and shape of activation function important for both.

• Static rivalry most consistent with escape (durations depend on mutual inhibition strength).

• Intermittent rivalry most consistent with release (durations do not depend on mutual inhibition strength).

• Breaks are good for dynamic-memory as well as noise (?)
These models have a major flaw. Rivalry is fundamentally stochastic.
Noise model for rivalry
Robust statistics for rivalry - data

Leopold and Logothetis, 1996

Cao, et. al 2016

\[ CV_{\text{ISI}} = \frac{\text{spike interval standard deviation}}{\text{spike interval mean}} \approx 1 \]
Balanced-state based on excitatory and inhibitory neurons balancing such that:

- mean input is at threshold
- spike generation is fluctuation driven
Can balanced-state and mutual inhibition (net negative) coexist as a model for perceptual rivalry?

Two candidate rivalry (mutual inhibition) and balanced-state frameworks.
Mutual inhibition vs the balanced-state

Models reproduce realistic spiking with no added noise term.

Irregular spiking

Asynchronous spiking
Models reproduce realistic percept duration variability with no added noise term.
Models capture mean dynamics.
Mutual inhibition vs the balanced-state

What is the mechanism for variability?
Balanced-state?
What is the mechanism for variability?
Balanced-state? Yes and no
Under some conditions (that can be relaxed) in the limit of large $N$, balanced-state becomes a linear problem.

\[ \begin{align*}
wee r_e - wei r_i + f_e &= 0 \\
wie r_e - wi i r_i + f_i &= 0
\end{align*} \]
Mutual inhibition vs the balanced-state

How well does this fit?

dominant excitatory population

- simulation
- classic balanced state theory

rate (Hz)

$W_{ie_{long}}$

0 5 10 15 20 25 30 35 40 45 50 55 60 65 70
How well does this fit?
Mutual inhibition vs the balanced-state

How well does this fit?

dominant excitatory population

- simulation
- classic balanced state theory
- mutual-inhibition balanced state theory

rate (Hz)

$W_{ie_{long}}$
How well does this fit?
• Self-consistent model explains spiking and perceptual variability and percept mean dynamics.

• Supports a noise model for rivalry that is cross-multiplicative from balanced-state dominant pool.

• Suggests mutual inhibition balanced-state model for none winner-take-all but competitive psychophysics.
CLINICAL PICTURE
Some clinically interesting features of rivalry:

- measure of cognitive stability
- assess structure of percept state-space
- capture effective biological parameters
Clinical Research of Rivalry

Studied for many decades in many clinical contexts with many positive associations:

most major mental illnesses - schizophrenia, bipolar disorder, major depression, autism

many pharmacological agents - caffeine, benzodiazepine, catecholamine, psilocybin

but limited interpretation and utility due to task design
Need to modernize clinical studies

- Clinical studies are often point analyses.
- Need to capture the time-varying surface.
- Map the surface back to mechanistic model.
Dynamical systems look different depending on context. Need to deconvolve test-condition transformation on brain circuit.

\[ b(\beta, E) \] biological parameters of interest

\[ M(b(\beta, E)) \] external (context dependent) parameters

above embedded in report (measurement) function
Rivalry alone can “theoretically” identify 14 parameters, with self-report.

\[ \tau_{u_i} \frac{d u_i}{d t} = -u_i + g(S_i - \beta_j u_j - \gamma_i a_i) \]

where \( g(x) = [\max(0, x)]^{\eta_i} \)

\[ \tau_{a_i} \frac{d a_i}{d t} = -a_i + u_i \]

\( \tau_a \gg \tau_u \)

\( u_i := \) neural activity

\[ M(b(\beta, \{im1, im2, c1, c2\})) = \text{dominance distribution } T \]

\[ M(x) := \text{some report filter on } b(x) \text{ in context rivalry} \]

\[ T_i = -\tau_{a_j} \ln \left( \frac{S_j - \beta_j u_i}{\gamma_j u_j} \right) \]

Dominance activity:

\[ u_{i(j)} = g(S_{i(j)} - \gamma u_{i(j)}) \]
ML notes

• Optimization scheme needs to account for different operating regimes of the circuit.
• Add data from other tasks to augment model fitting.
**Current Work**

VR rig for psychophysical inputs

Report:
- self-report (trackpad, head position)
- neural recordings

Song and Vattikuti, 2019
CURRENT WORK

Percept durations
Image A (black)
Image B (gray)

self-report data

Derive gradients by hand
(Speeds up model fitting)

\[ \epsilon(p) = \sum_{i \in \{\text{conds}\}} \sum_{j=1}^{2} \frac{(D^2 - T^j_i(p))^2}{\sigma^2_{ij}} \]
CURRENT WORK

Percept durations
Image A (black)
Image B (gray)

self-report data + fit

Image B contrast

Derive gradients by hand
(Speeds up model fitting)

\[
e(p) = \sum_{i \in \{\text{conds}\}} \sum_{j=1}^{2} \frac{(D_j^i - T_j^i(p))^2}{\sigma_{ij}^2}
\]

\[
\frac{\partial e}{\partial a_k} = \tau_v \gamma_{jk} \left( S_j - \beta_{jk} u_j \frac{\partial u_j}{\partial a_k} + \beta_{jk} \frac{\partial u_j}{\partial a_k} \right)
\]

\[
\frac{\partial e}{\partial b_k} = \tau_v \gamma_{jk} u_j \frac{\partial u_j}{\partial b_k} = \tau_v \gamma_{jk} u_j \frac{\partial u_j}{\partial b_k}
\]

\[
\frac{\partial e}{\partial \tau_v} = \tau_v \gamma_{jk} \left( S_j - \beta_{jk} u_j \frac{\partial u_j}{\partial \tau_v} + \beta_{jk} \frac{\partial u_j}{\partial \tau_v} \right)
\]

\[
\frac{\partial e}{\partial \sigma_{jk}} = -\ln \left( \frac{S_j - \beta_{jk} u_j}{\gamma_{jk} \sigma_{jk}} \right) \delta_{ijk}
\]

\[
\frac{\partial e}{\partial S_j} = \tau_v \gamma_{jk} \left( \frac{1}{\gamma_{jk} \sigma_{jk}} (1 - \delta_{jk}) + \frac{S_j - \beta_{jk} u_j}{\gamma_{jk} \sigma_{jk}} \frac{\partial u_j}{\partial S_j} + \beta_{jk} \frac{\partial u_j}{\partial S_j} \right)
\]

\[
\frac{\partial e}{\partial \beta_{jk}} = -\ln \left( \frac{S_j - \beta_{jk} u_j}{\gamma_{jk} \sigma_{jk}} \right) \delta_{ijk}
\]

\[
\frac{\partial e}{\partial \tau_v} = \tau_v \gamma_{jk} \left( S_j - \beta_{jk} u_j \frac{\partial u_j}{\partial \tau_v} + \beta_{jk} \frac{\partial u_j}{\partial \tau_v} \right)
\]

\[
\frac{\partial e}{\partial \sigma_{jk}} = -\ln \left( \frac{S_j - \beta_{jk} u_j}{\gamma_{jk} \sigma_{jk}} \right) \delta_{ijk}
\]
**Circuit parameters as latent variables**

Disjoint models “islands”

\[ b(x) := \text{nonlinear brain model} \]

\[ \vec{E} := \text{environmental conditions} \]

\[ \vec{M} := \text{vector of measurement functions} \]

\[ \vec{y} = \vec{M}(b(\vec{\beta}_0), \vec{E}) \]

**Latent variables**

- Parameters for brain model
- Neural activity
  - Individual neurons
  - Cellular factors
  - Genetic factors
- Brain networks
The things we can do with these latent variables

1. Uncover patient trajectories in cognitive-biological space using **objective** parameters
   1. Learn about the course of disease
   2. Learn about interventions
   3. Predict risk of adverse event
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