Sensory decoding models

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Stimulus Neural response

“Encoding” Transform and represent sensory information
Stimulus Neural response Behavior

“Encoding” Transform and represent sensory information

“Decoding” Extract encoded information for estimation/decision/action

psychometric function

p(v |v )

P(v > v2)

estimation stage
decision stage
the scientist’s perspective

\[ P(\text{spikes} \mid \text{stim}) \]
The organism receives sensory responses, and must make judgements about the stimulus, remember it, or act on it.
• basic SDT
• likelihood from populations
(next week: Movshon lecture)
ML decoding

For neurons with homogeneous tuning curves $f_k(x)$ and independent Poisson spiking, ML gives:

$$\frac{\partial}{\partial x} \log p(N_k|x) = \sum_k N_k \frac{\partial}{\partial x} \log f_k(x) = 0$$
In the special case of Gaussian tuning curves, ML estimate is simply a sum of the peak locations of each tuning curve, weighted by the number of spikes

\[
\hat{x} = \frac{\sum_k N_k x_k}{\sum N_k}
\]
In the special case of von Mises tuning curves (exponential of cosine), ML estimate is angle of a vector computed as the weighted sum of unit vectors in the peak direction of each tuning curve, weighted by the number of spikes

\[ \hat{\theta} = \angle \sum_k N_k u_k \]
“vector” decoding
[Kalaska, Caminiti Georgopoulous, 1983]

A sum of vectors, weighted by firing rate, predicts arm movement...
Visual motion

• Physiology: “motion pathway” heavily studied; arguably the strongest extrastriate success story.

• Perception: Human motion perception heavily studied. Humans are adept at tasks which require motion processing.

• Provides a rich source of visual information for prediction, depth perception, material properties, etc [Gibson, 1950]
Optic flow

[Gibson, 1950]
Fig. 1. Three different motions that produce the same physical stimulus.

Note that in all three cases the appearance of the moving grating, as seen through the window, is identical: the bars appear to move up and to the left, normal to their own orientation, as if produced by the arrangement shown in Fig. 1A. The fact that a single stimulus can have many interpretations derives from the structure of the stimulus rather than from any quirk of the visual system. Any motion parallel to a grating's bars is invisible, and only motion normal to the bars can be detected. Thus, there will always be a family of real motions in two dimensions that can give rise to the same motion of an isolated contour or grating (Wohlgemuth, 1911, Wallach, 1935; Fennema and Thompson, 1979; Marr and Ullman, 1981).

Figure: Movshon, Adelson, Gizzi, Newsome, 1985

“Aperture Problem”
Intersection-of-constraints (IOC)

Fig. 4. A single grating (A) and a 90 deg plaid (B), and the representation of their motions in velocity space. Both patterns move directly to the right, but have different orientations and 1-D motions. The dashed lines indicate the families of possible motions for each component.

[Adelson & Movshon, 1982]
Movshon, Adelson, Gizzi & Newsome, 1985
Visual motion ambiguity
Simple plaid perception = IOC

[Adelson & Movshon, 1982]
Simple plaid perception = IOC

[Adelson & Movshon, 1982]
IOC failure

[Stone et al. 1990]
The “Thompson effect”

Contrast affects perceived speed

[Thompson ‘82]
Helmholtz (1866)

Perception is our best guess as to what is in the world, given our current sensory input and our prior experience [paraphrased]
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Helmholtz (1866)

Perception is our best guess as to what is in the world, given our current sensory input and our prior experience [paraphrased]
Bayesian perception

world

measurement

noise!

observer

estimate

memory
Bayesian perception

world

measurement

noise!

memory

observer

\[ P(m|v) \]

likelihood

P(m|v)
Bayesian perception

\[ P(m|v) \quad P(v) \]
Bayesian perception

world

observer

measurement

estimate

no noise!

prior

probability

P(m|v)  P(v)
Bayesian perception

\[ P(m|v) \times P(v) \sim P(v|m) \]
Bayesian perception

world

measurement
noise!

observer

estimate

prior

probability

v

\[ v \]

\[ \hat{v} \]
Bayesian perception

world

observer

measurement

noise!

prior

estimate

probability vs. $v$

probability vs. $\hat{v}$
Some Bayesian perceptual models

- Shading/lighting [Kersten 90; Knill, Kersten, Yuille 96; Mamassian, Landy, Maloney 01]
- Motion [Simoncelli 93; Weiss et al. 02; Stocker & Simoncelli 06]
- Surface orientation [Bülthoff & Yuille 96; Saunders & Knill 01]
- Color constancy [Brainard & Freeman 97]
- Contours [Geisler, Perry, Super 01]
- Sensory-motor tasks [Körding & Wolpert 04]
Brightness Constancy

• Assume translational motion (locally)

• Differential approximation (Taylor series)

\[ \nabla I \cdot \vec{v} + I_t = 0, \quad \nabla I = [I_x, I_y] \]

• Insufficient constraint, so combine over a neighborhood (space and/or time):

\[ \min \sum (\nabla I \cdot \vec{v} + I_t)^2 \]

[Fennema & Thompson ‘79; Horn and Schunck ‘81]
With noise...

• Additive Gaussian noise in temporal derivative:

\[ \vec{\nabla} I \cdot \vec{v} + I_t = n \]

• Likelihood (combined over neighborhood):

\[ P(\vec{\nabla} I, I_t|\vec{v}) \propto \exp[- \sum (\vec{\nabla} I \cdot \vec{v} + I_t)^2 / 2\sigma^2] \]

[Simoncelli, Adelson, Heeger ‘91]
With prior...

• Simplest prior choice: Gaussian (preference for slow speeds)

\[ P(\vec{v}) \propto \exp\left[-||\vec{v}||/2\sigma_p^2\right] \]

• Posterior:

\[ P(\vec{v}|\vec{\nabla}I, I_t) \propto \exp\left[-||\vec{v}||/2\sigma_p^2 - \sum(\vec{\nabla}I \cdot \vec{v} + I_t)^2 / 2\sigma^2\right] \]

[Simoncelli, Adelson, Heeger ‘91]
Idealized illustration of ambiguities
Idealized illustration of ambiguities

Bayesian posteriors
(Gaussian noise, Gaussian prior)
stimulus

[Simoncelli & Heeger, ARVO ‘92]
Stone et al. 1990

Model

Subject

Log Contrast Ratio

Perceived Direction Bias (degrees)

[Simoncelli & Heeger, ARVO ‘92]
stimulus

[Simoncelli & Heeger, ARVO '92]
Ferrera & Wilson, 1991

Perceived Speed (relative to IOC)

Plaid angle (degrees)

- Subject2
- Model
- Cosine

[Simoncelli & Heeger, ARVO ‘92]
Stone & Thompson, '90

max contrast 70%
max contrast 40%

Stone et al, '90

Bias(degrees)

Feature motion
Normal motion

Lorenceau et al, '92

Percent correct

Yo & Wilson, '92

Direction (degrees)

Burke & Wenderoth, '93

Judged plaid direction

Bowns, '96

Plaid component separation (degrees)

Percentage in VA direction

[Weiss, Simoncelli, Adelson, '02]
Credits

• Bayesian Plaid motion modeling: Edward Adelson, David Heeger, Yair Weiss

• Reverse-engineered prior/likelihood: Alan Stocker