Ideal Observers and Ideal Actors

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Ideal Observers / Ideal Actors

- Q: What is the “optimal” performance on a perceptual/cognitive/motor task?
  - Given the information available in the environment, what is the best possible performance on a task?
- Ideal Observer / Ideal Actor
  - Fully informed
  - Infinite computational accuracy
  - Fully rational

Ideal Observers / Ideal Actors

- Valuable benchmark for evaluating human performance
  - If human = ideal, human using all available information in an efficient manner
  - If human < ideal, why?
    - What are limitations on human perceptual/cognitive/motor processing?
    - What training or manipulations can be done to improve human performance?

Ideal Observers / Ideal Actors

- <u>Caveat</u>: Definition of “optimal” based on assumptions!!!
  - Can have multiple definitions of optimal performance, each based on a different set of assumptions
- Modeling assumptions
  - About structure of graphical model
    - E.g., independence assumptions
  - About parametric forms of probability distributions
  - About prior probabilities
  - About loss functions

Outline

- Ideal Observers
  - Visual Motion Perception
  - Visual Contour Integration
- Ideal Actors
  - Adaptive Control in Different Noise Environments

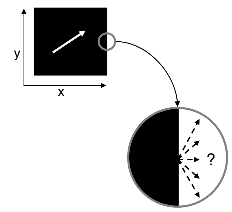
Motion Perception

- Problem: calculate 2D object velocity from a sequence of images
- We know based on the organization of the visual system that motion analysis begins with local measurements, such as the output of direction-selective cells in V1
- Local measurements must then be integrated to yield global motion percepts

Motion Perception

- Integration is essential because the initial local estimates are ambiguous
- Why are they ambiguous?
- Local estimates suffer from the “Aperture Problem”

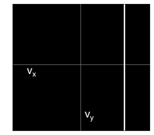
The velocity of a smooth contour viewed through an aperture is ambiguous



Only the magnitude of the velocity perpendicular to the translating edge can be measured

No intensity gradient is measured along the translating edge

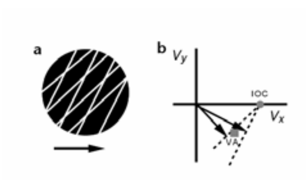
i.e., $-\frac{\partial I}{\partial t} = \frac{\partial I}{\partial x} v_x + (0) v_y$



The resulting (1D) measurement is consistent with an infinite set of (2D) velocities

Motion Integration

Simple example: integration of two components in plaids and rhombuses



- Heuristic solutions
  - Intersection of constraints (IOC)
  - Vector average (VA)

Motion Integration

- Human motion perception seems puzzling
- Performance sometimes consistent w/ IOC and sometimes w/ VA
- Strong dependence on relative orientation, speed, and contrast of components

Motion Integration

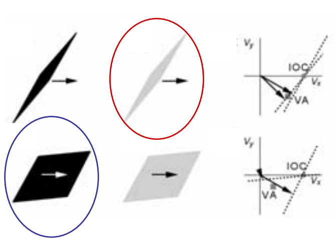
Example: translating rhombus

At low contrasts and with close component orientations, perception seems to be consistent with VA.

At high contrast and with distant component orientations, perception seems to be consistent IOC.

Percept consistent w/ VA

Percept consistent w/ IOC

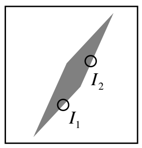


Optimal Motion Perception

- A better approach: Ideal observer model for motion perception
  - Weiss, Simoncelli, and Adelson (2002)
  - “Motion Illusions as Optimal Percpets”
- Key Assumptions:
  - Local image measurements are noisy
  - Image velocities tend to be slow

Optimal Motion Perception

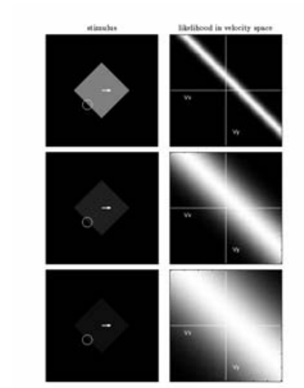
For simplicity, imagine that we get information from only two local image windows

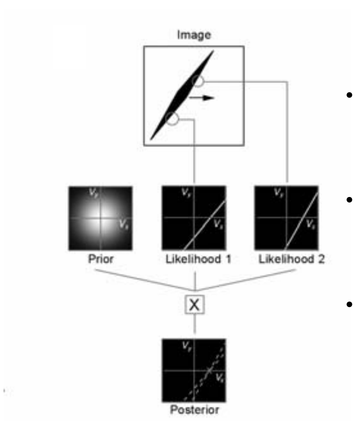


Now, the problem of estimating velocity looks like a cue-combination problem

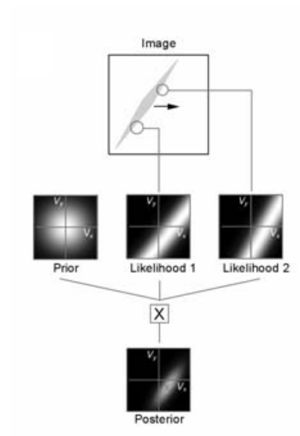
$$
\begin{aligned}
v^* &= \arg\max_v P(v \mid I_1, I_2) \\
&= \arg\max_v P(v)\, P(I_1 \mid v)\, P(I_2 \mid v)
\end{aligned}
$$

- Contrast affects the variance of the velocity estimates
- High contrast: narrow likelihood
- Low contrast: broad likelihood

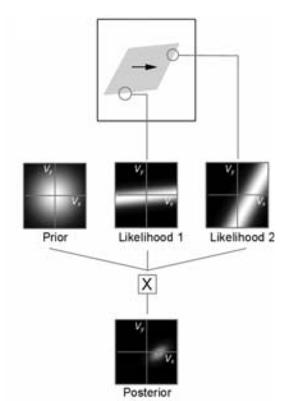




- Thin, high-contrast rhombus
- Tight likelihoods dominate broad prior
- Result: IOC-like percept



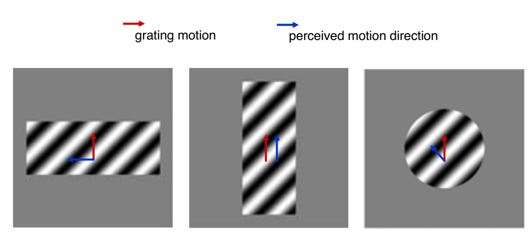
- Thin, low-contrast rhombus
- IOC velocity has high magnitude
- Broad likelihoods, posterior influenced by prior
- Result: posterior pulled toward lower speed velocity consistent w/ VA



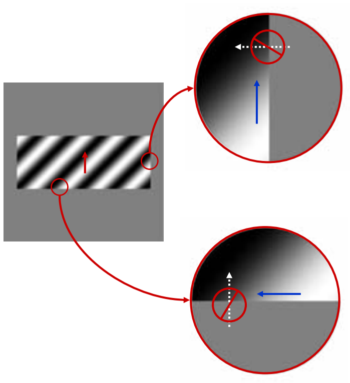
- Fat, low-contrast rhombus
- IOC velocity has low magnitude
- Broad likelihoods, posterior influenced by prior
- Result: posterior pulled toward lower speed but direction still consistent w/ IOC

Another Example: The “barberpole” illusion

The perceived motion of a simple grating translating behind an aperture changes with the aperture’s shape



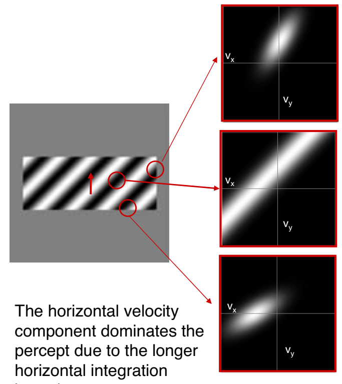
At the edges of the aperture, local velocities are disambiguated by 2D motion signals



Vertical aperture edges create a motion signal consistent with a vertically moving “corner”

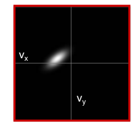
Horizontal aperture edges create a motion signal consistent with a horizontally moving “corner”

Local likelihoods

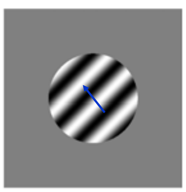


The tighter likelihoods at the aperture boundaries dominate both the broad prior and the underconstrained likelihood in the center

The horizontal velocity component dominates the percept due to the longer horizontal integration boundary

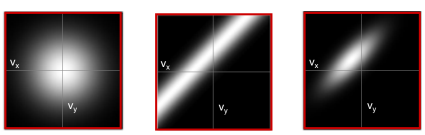


Posterior



For a circular aperture, the effects of these boundaries is balanced

The prior dominates the ambiguous likelihood so that the MAP direction reflects the slowest velocity consistent with the constraint line



Prior | Likelihood | Posterior

Contour Integration

- People are great at segmenting noisy and cluttered scenes into objects
- This is due in part to our ability to group local edges into contours
- This ability has been studied by many researchers
  - Gestalt psychologists: “Good Continuity”
  - Field, Hess & Hayes: “Local Association Field”

Contour Integration

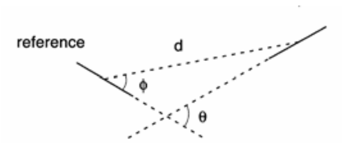
- Ideal observer for contour integration
  - Geisler, Perry, Super, and Gallogly (2001)
  - “Edge Co-Occurrence in Natural Images Predicts Contour Grouping Performance”
- How would an ideal observer determine whether a set of edges belong to the same contour?
- Simple approach: calculate probability that two edges belong to same contour and apply transitivity rule (Geisler et al., 2001)
  - Simplifying assumption: only pairwise edge statistics are important (pairwise approximation)

Measuring Edge Distributions for Natural Scenes

- Locate significant edges in natural images
- Label contour membership for each edge (ground truth)
- Measure conditional pairwise edge co-occurance statistics

$$P(d,\theta,\varphi | C)$$

(from Geisler et al., 2001)



- For each pair of edges in the image, determine
  - d, the distance between the edges
  - φ, the angle between the edges
  - θ, the difference in orientation between the edges
  - *C*, whether they belong to a common contour
- Use resulting histogram to estimate $P(d,\phi,\varphi | C)$

Contour Integration

Problem: Given a pair of edges e_1, e_2, decide whether they belong to a common contour. That is, determine

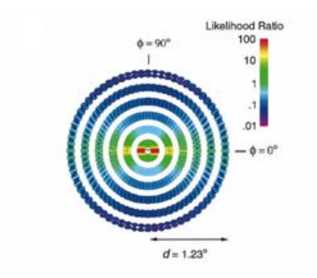
$$\arg\max_C P(C | e_1, e_2)$$

where *C=1* indicates that the edges belong to a common contour and *C=0* indicates that they do not.

Because C takes only two values, we can use a likelihood ratio test. The ideal observer decides that the edges belong together if

$$\frac{P(d,\theta,\varphi | C=1)}{P(d,\theta,\varphi | C=0)} > \frac{P(C=0)}{P(C=1)}$$

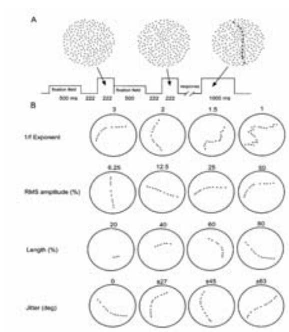
Measured Likelihood Ratios $\frac{P(d,\theta,\varphi | C=1)}{P(d,\theta,\varphi | C=0)}$



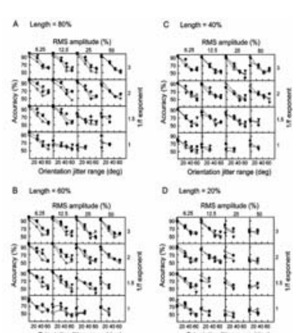
(from Geisler et al., 2001)

Contour Integration

- Geisler et al. (2001) used a contour identification task to compare the performance of the ideal and human observers
- 2IFC Task: determine which stimulus contained the longest contour
- Ideal observer used measured statistics and transitivity rule (if A→B and B→C, then A→C) to integrate edges



Contour Integration

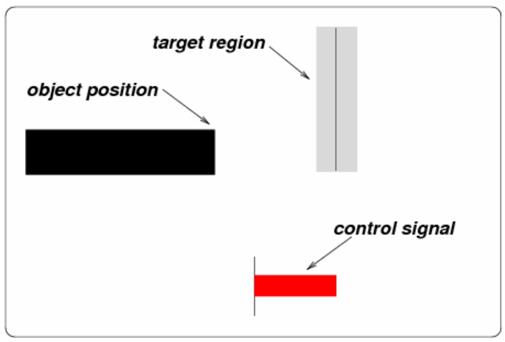


(from Geisler et al., 2001)

- Results
  - Closed figures represent human data
  - Open circles represent ideal observer data
- The ideal observer based on natural scene statistics accounts well for human data across many conditions

Dynamics and Noise

- Chhabra and Jacobs (2006)
- "Near-Optimal Human Adaptive Control Across Different Noise Environments"
- Adaptive control requires learning about both the <u>dynamics</u> and the <u>noise</u> of a complex system
- Dynamics: relationship between control signals and the expected responses to these signals
- Noise: relationship between control signals and the variances of the responses to these signals



Dynamics and Noise

- Dynamics: 2nd –order linear system

$$m\ddot{x} = f - b\dot{x}$$

  - Object position, velocity, acceleration: $x, \dot{x}, \ddot{x}$
  - Mass: *m*
  - Force: *f*
  - Viscous resistance: *b*

- Noise: corrupts force *f*

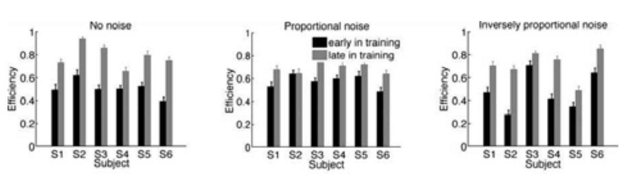
Three Noise Conditions

- No-Noise (NN)
- Proportional Noise (PN)
  - Small forces are corrupted by small amounts of noise
  - Large forces are corrupted by large amounts of noise
- Inversely-Proportional Noise (IPN)
  - Small forces are corrupted by large amounts of noise
  - Large forces are corrupted by small amounts of noise

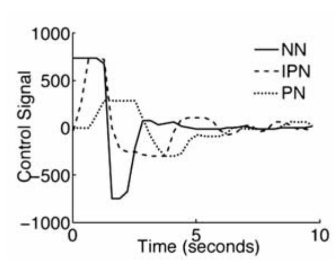
Ideal Actors

- Optimal control laws computed via dynamic programming
  - Optimal control law depends on the noise characteristics of the environment
  - Different ideal actors were created for different noise conditions
- Efficiency:
  - Ratio of subject's performance to expected performance of ideal actor

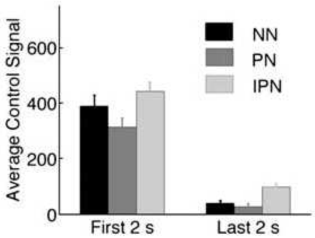
Experimental Results

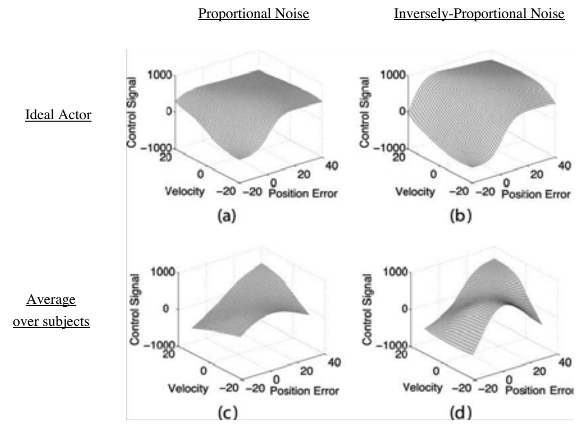


Experimental Results



Experimental Results





Results

- Subjects learned control strategies tailored to the specific noise characteristics of their conditions
  - Allowed them to achieve levels of performance near the information-theoretic upper bounds
- Conclude: Subjects learned to efficiently use all available information to plan and execute control policies that maximized performances on their tasks

Results

- Q: Is human adaptive control optimal across different noise environments?
- A: Yes (under the conditions studied here)

Summary

- Ideal Observers
  - Visual Motion Perception
  - Visual Contour Integration
- Ideal Actors
  - Adaptive Control in Different Noise Environments