Bayesian vision: The early years

Dan Kersten
David Knill Memorial Symposium
VSS 2015
The “state of affairs” ~ 1985

- Psychology
- Neuro-physiology
- Signal detection theory
- Computer vision
- Theoretical neuroscience
- Digital image processing & 3D graphics
The “state of affairs” ~ 1985
The “state of affairs” ~ 1985

ideal observer analysis

Psychology

Neuro-physiology

Signal detection theory

Theoretical neuroscience

Digital image processing & 3D graphics

Computer vision
The “state of affairs” ~ 1985

ideal observer analysis
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A Learning Algorithm for Boltzmann Machines*

1985
The “state of affairs” ~ 1985

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1983

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What was “Bayesian vision” back then?

• mathematics of inference given uncertainty

• common language to integrate disciplines

• tools to model image and scene regularities
What was “Bayesian vision” back then?

- mathematics of inference given uncertainty
- common language to integrate disciplines
- tools to model image and scene regularities

...beginning to hint as a set of conceptual and analytical tools to understand how humans infer causes (scenes, objects) from data (images)

In those “early days”, it was strongly motivated by the idea of perception as inverse optics
forward optics

\[ p(\mathbf{S}) \quad p(\mathbf{I} | \mathbf{S}) \quad p(\mathbf{I}) \]

\[ \text{prior} \quad \text{likelihood} \quad \text{the generative components} \]

Information about object properties is encrypted in the image.
Given a small intensity patch, what caused it in the scene?

Given a 2D image, which 3D shape?

From Sinha & Adelson
Given image pattern I, what combinations of lights, material, object properties (S) caused it?
vision as inverse optics

Given image pattern I, what combinations of lights, material, object properties (S) caused it?

Bayes theorem

\[ p(S \mid I) \propto p(I \mid S) \cdot p(S) \]

- likelihood modeled using forward optics
- prior assumed or measured properties of scenes
shape from shading

1986-87: Dave, student “glue”

Jim Anderson  Dave  Dan Kersten
image intensities

the “shape from shading” problem

perceived geometry?
the “shape from shading” problem

perceived geometry?

image intensities

\[ p(S \mid I) \propto p(I \mid S) \cdot p(S) \]

- lambertian, single light source, fixed view
- fractal
the “shape from shading” problem

perceived geometry?

exploit the generative aspect of Bayes

image intensities

\[
p(S | I ) \propto p(I | S ) p(S)
\]

lambertian, single light source, fixed view

fractal
generate lots of surfaces in 3D

render the surfaces to make lots of images

fractal prior

3D to 2D projection
Use supervised learning to construct an estimator for 3D surface shapes

Use supervised learning to construct an estimator for 3D surface shapes

an interesting method...but how to take this forward to explain human perception of shape, object properties?

perhaps there were bigger issues...

the causes of image patterns were more complicated e.g. discontinuities are important, but causes of discontinuities are not all the same
lightness as reflectance estimation

1988-91: Dave, precocious experimentalist and “closer”
mechanistic view

Convolve with Mexican-hat filter, e.g. via lateral inhibition

Threshold and de-convolve, i.e. re-integrate
mechanistic view

causal view

Image Luminance
reflectance $\times$ illumination

Reflectance

Illumination

piece-wise constant prior

spatially smooth prior
inferring causes

Image Luminance

Reflectance

X

Illumination

point

ambient
causal view

Image Luminance

Reflectance

Shape

Illumination

Reflectance

Shape

Illumination
“harumph!”
(anonymous senior professor)
“harumph!”
(anonymous senior professor)

“An expression of disdain, disbelief, protest, refusal or dismissal” - en.wiktionary.org
Dave’s response

Use 3D graphics to make the stimuli

Do psychophysics with an indirect matching task of lightness

contours, shape (and material)

1988: Dave goes solo
contours, shape (and material)

1988: Dave goes solo

the “geodesic” constraint
same interior shading pattern
different contour shapes

matte

appears more specular
same interior shading pattern
different contour shapes

same interior shading pattern
different contour shapes


Minnesota: 1990-1994

Zili Liu, Pascal Mamassian, Wendy Braje, Suthep Madarasmi, Bosco Tjan.. 

Al Yonas, Irv Biederman, Gordon Legge 

Visiting professors: Heinrich Bülthoff, Alan Yuille, Mel Goodale
1991: Dave the seer

“Maybe the brain represents probability distributions, not just estimates” — Dave Knill, ca. 1991
“Maybe the brain represents probability distributions, not just estimates” — Dave Knill, ca. 1991
“Maybe the brain represents probability distributions, not just estimates” — Dave Knill, ca. 1991


The Chatham meeting and book

Ted Adelson, Horace Barlow, Peter Belhumeur, Bennett, Andrew Blake, Heinrich Bülthoff, Jacob Feldman, Bill Freeman, Stu Geman, Don Hoffman, Alan Jepson, Dan Kersten, Dave Knill, Pascal Mamassian, David Mumford, Ken Nakayama, Alex Pentland, Chetan Prakash, Whitman Richards, Scott Richman, Ron Rensink, Dave Sheinberg, Shin Shimojo, Alan Yuille

1993: Dave the organizer, integrator, and conversant

John Tangney, AFOSR
The Chatham meeting and book

1993: Dave the organizer, integrator, and conversant

John Tangney, AFOSR


..in closing

Dave the problem solver, not an ideologue

..by 1995, studies leading to some 17 articles, 10 as first or sole author
What is Bayesian vision today?  
...by 1998

No longer as simple as "inverse optics"
David Knill and the Rational Analysis of mid-level vision

Paul Schrater

Graduate student with Dave, 1994-1998
20 Years ago today

1995 University of Pennsylvania Psych Building

As a joke only we though was funny, all lab members wore that hat for lab profile pics.
Knill became almost synonym for the Bayesian Brain

- Ecological perception complex and ambiguous

- Ambiguity generates uncertainty which must be handled well to guide actions
Traditional Levels of Analysis

Computational
Why do things work the way they do?
What is the goal of the computation?
What are the unifying principles?

Algorithmic
What representations can implement such computations?
How does the choice of representations determine the algorithm?

Implementational
How can such a system be built in hardware?
How can neurons carry out the computations?

maximize:
$$R_t = r_{t+1} + r_{t+2} + \cdots + r_T$$
Illusion results from byproduct of early sensory processing.
Illusion results from rational analysis of the scene
Dave was not Anti-Reductionist

- But some complain that a Bayesian approach is “vague” and of “questionable merit”

‘While Marr’s original attack on reductionism was justified it is no longer tenable’
Some properties of a useful psychophysical framework

- Support building predictive models of perceptual performance.
- Support bridging statements between models and descriptions of behavior.
- Explain “why” perception / sensorimotor control works the way it does.
- Help guide psychophysical research
  - Suggests new and interesting theoretical questions.
  - Supports scaling down perceptual / sensorimotor problems to bring them into the lab.
  - Scales up naturally
World model
Sensory processing

Generative model

World model

Information

Noise

Sensory processing

Sensory Features

Slide from Dave’s talk at Battaglia and Schrater’s 1998 VSS symposium
Slide from Dave's talk at Battaglia and Schrater's 1998 VSS symposium

World model

Generative model

Bayesian Computations

p(S | I)

Sensory processing

Noise

Sensory Features
Slide from Dave’s talk at Battaglia and Schrater’s 1998 VSS symposium
Slide from Dave’s talk at Battaglia and Schrater’s 1998 VSS symposium

- Sensory processing
- Sensory Features
- Noise
- Bayesian Computations
- World model
- Generative model
- Ideal Observer

```
p(S | I)
```

Task model

Estimate

Bayesian Computations

Sensory Features
Slide from Dave's talk at Battaglia and Schrater's 1998 VSS symposium

World model

Sensory processing

Generative model

Noise

Bayesian Computations

Ideal Observer

Task model

Estimate

$p(S | I)$
Ideal observer models

Rational observer models

The domain of Bayesian models

Description of sensorimotor / perceptual behavior
Threefold Knowledge

1) Image physics
2) Environmental regularities
3) Human task requirements
Generative model

- Sample a **scene type**
- Sample **N** object classes
- Sample **Objects** from each class (locations and attributes for each object)
- Sample **rendering variables** (lights, viewpoint)
- Sample **image features** from rendered scene
Rational Analysis for Mid-level vision

• What are the evolutionary pressures and environmental features that shape perception?
• These lead to a family of computational problems
  – Natural visual tasks and behavior
    • Getting reliable estimates of object geometry and material
  – Statistical structure of the environment
    • What regularities can be exploited?
Ideal observer analysis

How well can any observer compute surface orientation from texture?

“Surface orientation from texture: ideal observers, generic observers and the information content of texture cues” Vision Research, 1998
Knowledge needed

• Geometric
Knowledge needed

• Geometric

• Statistical

Homogeneity/isotropy
Defining “Cues”

Elliptical Approximation
Defining “Cues”

Elliptical Approximation

3 parameters
Defining “Cues”

Elliptical Approximation

... Per element
Defining “Cues”

Elliptical Approximation

3 parameters

... Per element

Voila! Cues!

Add spatial gradient
People kind of suck, but that’s expected!
Why so BAD?

People barely improve with FOV

=> Not much of image is used
Natural “reverse correlation”

Natural Cue fluctuations

\[ f(\text{trials}) \rightarrow \text{slant} \]

Bayesian Estimation with Family of observer models

Cue weights
Cue weights

Fig. 3. The signal detection model we used for our analysis (see text for description).
Change strategy with environmental regularities

Increasing texture compression
What are cue weights?
What are cue weights?

• Summary descriptions of perceptual performance.
What are cue weights?

• Summary descriptions of perceptual performance.
• Summary descriptions of the information available for a task.
What are cue weights?

- Summary descriptions of perceptual performance.
- Summary descriptions of the information available for a task.
- Support logical links between behavior and rational/normative models of performance.
Texture information

Least Reliable

Most Reliable

Binocular information

Equally reliable
Humans weight sensory cues “optimally”

- Discrimination thresholds in single cue conditions predict weights measured in multi-cue experiments.
  - Ernst and Banks, 2002; Knill and Saunders, 2003; Alais and Burr (2004); etc., etc., etc.
Humans weight sensory cues “optimally”

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  - Ernst and Banks, 2002; Knill and Saunders, 2003; Alais and Burr (2004); etc., etc., etc.

### Linear process model

- Texture data \((I_t)\)
- Stereo data \((I_s)\)

\[
\begin{align*}
\text{Slant from texture} & \quad S_t \quad w_t \\
\text{Slant from stereo} & \quad S_s \quad w_s
\end{align*}
\]

\[S_t + S_s \rightarrow S_{st} \rightarrow \text{Action / Decision}\]
Humans weight sensory cues “optimally”

- Discrimination thresholds in single cue conditions predict weights measured in multi-cue experiments.
  - Ernst and Banks, 2002; Knill and Saunders, 2003; Alais and Burr (2004); etc., etc., etc.

### Linear process model

- Texture data \( (I_t) \) → Slant from texture → \( S_t \) → Action / Decision
- Stereo data \( (I_s) \) → Slant from stereo → \( S_s \)

\( S_{st} \) = \( w_t S_t + w_s S_s \)
Why depth?
Depth cues: Vision vs. Motor Control

(a) Visuomotor versus perceptual cue weights
(b) Effect of visual feedback
(c) Effect of experience
My Work: Complex inference in reaching to depth

Nodes: random variables
\( X_1, \ldots, X_4 \)

Each node has a conditional probability distribution

Links: direct dependencies

Data: observations of \( X_3 \) and \( X_4 \)

\[ P(X_1, X_2, X_3, X_4) = P(X_4 | X_2) \ P(X_3 | X_1, X_2) \ P(X_1) \ P(X_2) \]

**EXAMPLE**

\( X_1 \) object size
\( X_2 \) object distance
\( X_3 \) image size
\( X_4 \) “felt” distance
Main Lesson: *Theory Matters*

It’s not a theory of vision unless it can handle real stimuli and tasks

– *Functional analysis*
  - *Why and what come before How*
  - Develop whatever theory you need

– Design airtight psychophysical experiments
  - **BUT** *Embed experiments in near-ecological contexts*
Dave’s Impact

• Professional
  – Key champion of computational level modeling
    • Why do we have vision at all?
    • What’s the brain for?
    • Only given it’s purpose can you make sense of details
  – Key champion of Bayesian analysis
  – Combined rigor, depth and hard problems like very few in the field can. Tough act to follow.

• Personal
  – Taught me how to balance high standards with the joy of discovery
  – How to concoct a story on the spot
  – Never prepare a talk before the night before!
With enough details, all are credulous

- Chinese influence on the origins of Appalachian folk music
Knill has recently completed a series of studies that examines the role of texture in the perception of orientation. Texture cues indicate surface orientation vis-a-vis the change in shape associated with more distant vs. nearer elements. For example, the grade of a cobblestone road is cued in part by changes in the size and shape of the road elements.

Knill’s work indicates that changes in both size and shape of the texture elements contribute to the sense of surface tilt, and that the contributions are approximately equal.

In collaboration with Tjeerd Dijkstra (IRCS postdoctoral fellow), an evaluation of the contribution of highly oriented textures, or texture flow, for the perception of orientation has begun. In the past year, Simoncelli and Knill have begun collaboration on experiments that evaluate the role of temporal deformations in the perception of the shape of texture patterns.
Theoretical Approaches to Multisensory Perception

Robert Jacobs
Department of Brain & Cognitive Sciences
Center for Visual Science
University of Rochester
Multisensory Perception

• Collaborating with Dave was productive and fun:
  – Experiment: Cue reliability and cue recalibration

• Dave loved talking about science. Not only his own science, but your science too:
  – Experiment: Generalization from perception to motor production
  – Implications for perceptual learning
Cue Reliability and Cue Recalibration

• Collaborators
  – Joseph Atkins (Colby College)
  – David Knill

“Touch Educates Vision”

- Bishop George Berkeley
  - *An Essay Towards a New Theory of Vision* (1709)

- Perception of visual space results from associations between visual sensations and sensations of touch and motor movement
  - “Touch educates vision”
Research Question

Question:

Can observers adapt their interpretations of a stereo cue on the basis of consistencies (and inconsistencies) between depth-from-stereo and depth-from-haptics percepts?
Visual Stimuli

• Scenes consisted of two fronto-parallel surfaces

• Narrow surface was closer to subject, and it occluded the middle portion of the wide surface

• Subjects viewed scene head-on (orthogonal view)

• Stereo only reliable visual cue to depth between two surfaces
Visual Stimuli
Virtual Reality Environment
Procedure

• **Judgment**: Is width of front surface greater or less than the depth between the two surfaces?
  – Based on visual cues
  – Based on visual and haptic cues
  – No corrective feedback

• **Four stages**:
  – Consistent-cue training trials
  – Pre-test trials (visual information only)
  – Inconsistent-cue training trials
  – Post-test trials (visual information only)
Cue Conflict

- Independent control of:
  - Depth indicated by visual stereo
  - Depth indicated by haptics

- Trials with inconsistent cues:
  - Reaching distance greater than viewing distance by 60mm
  - Binocular disparities consistent with both reaching and viewing distances
    → Scaled depth between front and rear surfaces so that depth indicated by haptics > depth indicated by stereo
Prediction

• Based on inconsistent-cue training trials, subjects will adapt their depth-from-stereo estimates so that these estimates become more similar to their depth-from-haptics estimates
Experimental Results

- Subject TL:
Experimental Results

- Bishop Berkeley was right!
Multisensory Perception

• Collaborating with Dave was productive and fun:
  – Experiment: Cue reliability and cue recalibration

• Dave loved talking about science. Not only his own science, but your science too:
  – Experiment: Generalization from perception to motor production
  – Implications for perceptual learning
Generalization from Perception to Motor Production

• Collaborators:
  – Daniel Meegan (University of Guelph)
  – Richard Aslin (University of Rochester)

Generalization From Perception to Motor Production

• Experiment:
  – Motor production tests (Tasks 1 and 2)
  – Perceptual training
  – Motor production tests (Tasks 1 and 2)
Generalization From Perception to Motor Production

- Motor production tasks:
  - Produce two finger taps separated by a target temporal interval
    - Task 1: target interval = 300 ms
    - Task 2: target interval = 500 ms
  - Feedback: actual temporal interval
Generalization From Perception to Motor Production

- Perceptual training:
  - Auditory temporal interval duration discrimination task
    - Temporal intervals indicated by 2 auditory tones
  - On each trial, subjects heard two intervals (standard and comparison) and judged which one was longer
    - Group 1: standard interval = 300 ms
    - Group 2: standard interval = 500 ms
Generalization From Perception to Motor Production

• Prediction:
  – Subjects will show more motor improvement when the temporal requirements of the perceptual and motor tasks are identical

• Subjects trained to perceptually discriminate 300 ms (500 ms) intervals from other intervals will show the most improvement on producing 300 ms (500 ms) intervals
Subjects showed more motor improvement when the temporal requirements of the perceptual and motor tasks were identical.
Implications for Perceptual Learning

• Cross-modal transfer
  – Acquire knowledge about the environment through one sensory modality
  – Apply acquired knowledge when the environment is sensed through a different sensory modality

• Example: If you learn to visually categorize a novel set of objects, you can also often categorize the same (and similar) objects when they are grasped but not seen (Yildirim & Jacobs, 2013)
Implications for Perceptual Learning

• To us, cross-modal transfer and transfer from perception to motor production are closely related phenomenon
  – Both suggest the existence of amodal representations

  – If so, then experiment on transfer from perception to motor production has implications for perceptual learning
Narrow vs. Broad Generalization

• Perceptual learning
  – Many studies report that perceptual learning is often stimulus-specific (narrow generalization)
  – However...cross-modal transfer of knowledge is, by definition, not stimulus-specific

• Q: When is generalization narrow and when is it broad?
Are People Biased Toward Cross-Modal Transfer?

- In our experiment, subjects simultaneously generalized both narrowly and broadly
  - Narrow
    - Transfer of learning better for trained temporal interval
  - Broad
    - Transfer of learning from perception to motor production

- Hypothesis: Cross-modal transfer has a privileged status
  - People are biased toward generalizing cross-modally even under circumstances in which they simultaneously fail to generalize (or generalize narrowly) along other dimensions
Thank you!!!
Looking back and moving forward:
Dave Knill’s contributions to visual memory and motor control

Chris R. Sims
Knill Lab, ~2009–2013

Bo Hu

Amanda Yung

[Chris Sims

[Oh-sang Kwon

[Lindsay Bronnenkant, Laurel Issen, Leslie Lynch, Xaq Pitkow, Masih Ramati, Thomas Thomas, Indu Vedamurthy]
What I learned from Dave Knill

1. Think harder

2. Don’t be satisfied with inelegant solutions

3. Enjoy the journey
Outline (aka, this is an impossible task)

- Sensorimotor control and coordination


- Visual memory


Sensorimotor control

\[
\hat{x} = f(x_{obs}) \quad \text{State estimation}
\]
\[
u = g(\hat{x}) \quad \text{Feedback control law}
\]
\[
\mathcal{L} = h(x, u) \quad \text{Cost function}
\]

Goal: Minimize $\mathcal{L}$ w.r.t. $f, g$
Stochastic optimal feedback control
Stochastic optimal feedback control
The results of the current experiment provide the first direct evidence for continuous, on-line visual control of the moving hand that extends throughout the course of reaching movements. We hope that these results will help to settle the long-running debate concerning the role of visual feedback in the control of reaching movements. The technique of perturbing a virtual hand during reaching movements provides a promising tool for further exploring the nature of the visual feedback that the brain uses to control reaching movements.”

(Saunders & Knill, 2003)*

* Research also presented at first VSS meeting in 2001
Sensorimotor coordination

A

B

C

Uncertainty

Estimated

Actual
Sensorimotor coordination

- Observed
- Unobserved
- Estimated
- Actual
Sensorimotor coordination

- Observed
- Unobserved
- Estimated
- Actual
Experiment

- Task: Sort a bunch of objects into two piles
- Demands on vision:
  - Motor guidance
  - Information acquisition/planning
- Manipulate:
  - Difficulty of motor task
  - Difficulty of perceptual discrimination
- Examine adaptive timing of eye movements

(Sims, Jacobs, & Knill, 2011)
Saccade timing as utility maximization

(Sims, Jacobs, & Knill, 2011)
Motor control may be viewed as a problem of maximizing the utility of movement outcome in the face of sensory, motor and task uncertainty. Viewed in this way, and allowing for the availability of prior knowledge in the form of a probability distribution over possible states of the world, the choice of a movement plan and strategy for motor control becomes an application of statistical decision theory. This point of view has proven successful in recent years in accounting for movement under risk, inferring the loss function used in motor tasks, and explaining motor behavior in a wide variety of circumstances.

(Wolpert & Landy, 2012)
II. Perceptual memory

Memory as Bayesian inference?
Memory as Bayesian inference?

![Diagram](image.png)

- **Stimulus** $x$
- **Memory** $y$
- **Prior** $p(x)$

Probability density

Signal
Memory as Bayesian inference?

![Bayesian Inference Diagram]

- **Stimulus** \( x \)
- **Posterior** \( p(y | x) \)
- **Prior** \( p(x) \)
- **Memory** \( y \)

Signal

Probability density
Memory as Bayesian inference?

$$x \sim \text{Normal} \left( \mu, \sigma_x^2 \right)$$

$$y \mid x \sim \text{Normal} \left( x, \sigma_y^2 \right)$$

Memory = \textcolor{white}{\textit{p}(x \mid y) ?}
Memory as Bayesian inference?

(Ma, Husain, & Bays, 2014)
Memory as Bayesian inference

Efficient communication

Goal: Minimize $\mathcal{L}(x, y)$ w.r.t. $p(y | x)$ subject to $I(x, y) \leq C$

$p(x)$: Visual statistics
$\mathcal{L}(x, y)$: Cost function
$C$: Channel capacity
Memory as efficient communication

\[ p(x) = \text{Normal}(\mu, \sigma) \]
\[ \mathcal{L} = (y - x)^2 \]
\[ C = \frac{C_{\text{tot}}}{n} \]
What is the cost of misremembering?

- Different cost functions imply different optimal distributions of memory error, given the same channel capacity.
What is the cost of misremembering?

(Sims, 2015; JOV)
Looking back and moving forward

(Trommershaüser, Maloney, & Landy, 2008)
Vision lost and regained

Impact on direction of heading estimates from optic flow

Laurel Issen, Krystel Huxlin and David Knill
Vision lost after V1 damage

Visual field defects

- Partial Cortical Blindness
- Hemianopia

Loss of conscious vision

- Optic nerve
- Optic chiasm
- dLGN
- Optic radiation
- Striate cortex (V1)
- Extra-striate visual cortical areas (V2, V3, V4, V5, V7, etc)

Diagram showing visual field defects on the left and right eyes.
Damaging V1 – hemianopia

Causes:
Stroke – PCA, MCA
Tumors
Trauma, incl. TBI

Incidence:
0.8% population > 49 yrs old
(Blue Mountains Eye Study, Australia)
Up to 50% of stroke victims

Prognosis:
Spontaneous improvements in first 2-3 months
Deficit stable and permanent after that
Dogma: blindness cannot be recovered
Why damaging V1 causes blindness?

Residual visual processing after V1 damage

**Blindsight** (Weiskrantz et al., 1974; Weiskrantz, 1986) has an unconscious ability to detect, match, discriminate orientation, wavelength, speed (Morland et al., 1999).

But “blindsight” is **not** seeing

In spite of blindsight, even *unilateral* V1 damage dramatically alters visually-guided functions in daily life:

- Difficulties reading
- Inability to drive
- Bumping into objects
- Difficulties navigating

**WHY?**
Optic flow

Warren & Kurtz, 1992
Crowell & Banks, 1996

Contributes to walking
Warren et al., Nat Neuro 2001

May not contribute to walking
Rushton et al., Curr Bio 1998
Harris and Bonas, Vis Res 2002

Contributes to walking depending on fidelity of info
Li & Niehorster, J Neurophys 2014
Li et al., JOV 2014
How impaired are hemianopes at estimating direction of heading (DOH) from optic flow?

- How well do normal observers estimate DOH from optic flow when focus of expansion is obscured?
- How important are 4 quadrants/2 hemifields of vision in DOH estimation?
Experimental paradigm for direction of heading estimation task

Issen, Huxlin & Knill, JOV 2015
Experimental paradigm for direction of heading task

Anchor trial with DOH at 6°

Anchor trial with DOH at 3°

Perturbation trial

Issen, Huxlin & Knill, JOV 2015
Intact humans are *almost* ideal observers

They give weight to different visual field quadrants according to relevance of information content for DOH task

*Issen, Huxlin & Knill, JOV 2015*
How impaired are hemianopes at estimating DOH from optic flow?

Characterize and model behavior

- *Can the effects of hemianopia be modeled by simulating field loss?*
- *Are heading estimates in the intact visual field affected by hemianopia?*
- *We know hemianopes can “sense” some motion in their blind field – is it used for DOH tasks?*
Estimating impact of hemifield loss
Estimating impact of hemifield loss

Subjects: visually-intact controls (8 young, 8 older) and 7 hemianopes (older)

800 trials: perturbation (in left or right hemifields), anchor and feedback trials

Conditions: full field or simulated hemianopia (for older controls)
Older adults’ DOH estimates are more compressed towards fixation

8 young adults: 18-21 yrs, mean 19 yrs

8 older adults: 54-75 yrs, mean 68 yrs

○ Real target position
△ Perceived target position
Analyzing DOH estimates

\[
x_{\text{estimate left}} = \alpha_{\text{left}}[w_{\text{left}}^* x_{\text{left}} + w_{\text{right}}^* x_{\text{right}}] + \beta_{\text{left}} + \text{noise}
\]

\[
x_{\text{estimate right}} = \alpha_{\text{right}}[w_{\text{left}}^* x_{\text{left}} + w_{\text{right}}^* x_{\text{right}}] + \beta_{\text{right}} + \text{noise}
\]

\begin{itemize}
  \item $x$: X-coordinate of response
  \item $\alpha$: Compression/expansion factor
  \item $w^*$: Weight given to hemifield, normalized
  \item $\beta$: Additive response bias
\end{itemize}
All adults give more weight to hemifield containing DOH

Young

Older

Additive bias

Relative Weight

Comp/exp. factor

0.0

1.0

1.5

0.5

Young adults

Old adults

Right hem.

Left hem.

Young adults

Old adults

Relative Weight

0%

25%

50%

75%

100%

Young adults

Old adults

□ to opp. hem.

□ to DOH Hem.
Simulating hemianopia changes bias and compression

Average

Simulated hemianopia

Comp./exp. factor

Full field

Vis.

Blind

DOH in

Additive bias

-3.0
-2.0
-1.0
0.0
1.0
1.5
-3.0
-2.0
-1.0
0.0
1.0
1.5

s1
s2
s3
s4
s5
s6
s7
s8

Average
Real hemianopia alters compression and bias in BOTH hemifields
Some hemianopes give weight to blind field information when it contains DOH.
Summary

Hemianopes are impaired at estimating direction of heading from optic flow

- **Simulated** hemianopia underestimates real behavior
- Deficit affects **intact** hemifield performance
- Weight is given to **blind** hemifield information

Implications?

Real hemianopia is more exaggerated than simulated deficit

*Adaptation over time since stroke, additional factors?*

DOH judgments impaired across whole hemifield

*May explain persistent problems navigating*

Some hemianopes give significant weight to blind field information - automatically

*Improving motion processing in the blind field could help DOH estimation*
Acknowledgments

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Thank you!
Dave's work on mixture priors and causal inference

Wei Ji Ma
New York University
Mixture models and the probabilistic structure of depth cues

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Fig. 10. Stimuli for the experiments were created in three stages. First, a random, isotropic texture pattern was generated. This was then stretched by some amount in the vertical direction. The resulting texture was projected into the image at a slant of 65° and a vertical tilt. A subject that assumes surface textures are isotropic would overestimate the slant of the top stimulus and underestimate the slant of the bottom one.
Two (or more) categorically different scenarios that could have given rise to the sensory observations.
The role of memory in visually guided reaching

Anne-Marie Brouwer

David C. Knill

Center for Visual Science, University of Rochester, Rochester, NY, USA

Anne-Marie Brouwer
Masking flicker
Memorized location

Visual location
Flicker to extend the time that reflects information used for planning.
"I was a postdoc of Dave's. I had my job interview at VSS 2005, in the sun. Dave immediately struck me as a very friendly, thoughtful person. Even though in Rochester the environmental circumstances were quite different (no windows in the whole department!), Dave indeed turned out to be the friendly, thoughtful person consistent with my first impression, and so much more. To me he represents the true scientist, who wholeheartedly wants to get at the bottom of it, rather than being distracted by status and petty politics. I very much value the time spent in his lab, and will not forget our discussions and the occasional TGIF, having a beer with Ross, Hal, Brian, Bo and Dave amidst the experimental setups (-: ")

Anne-Marie Brouwer
(Dave's postdoc from Sep 2005 - May 2007)
2007-8: Extending to large jumps
Hi Dave,

I hope all is well. I would like to discuss with you if you would prefer me to step down from the project we have been doing together. I am well aware that between setting up my lab, writing grants, and preparing a course from scratch, I have neglected working on our project. Although I greatly enjoy it and would still be interested in carrying it through to a conclusion, unfortunately I do not anticipate having more than a few days a month to devote to it, as has been the case in the past half year. I can imagine that you need the results faster, or that you have students or postdocs who would be interested in this project. If that is the case, I do not want to be an obstacle. I could easily transfer my analysis files to someone else. Let me know!

Best,
Weiji
Hi Wei Ji,

Thanks for your thoughtful note. I'm afraid that I've been as bad as you about putting time into this - maybe we should both step down :). At the moment I do not have someone to step right into the breach, so it's ok with me if you want to stay with it. Right now, we seem to be in a place where we might have to re-design the experiments and collect more data. I understand, though, if you want to step down. Sometimes these side projects end up being more of a psychological burden than anything else. If you are feeling that way, I completely understand and I'm ok with you stepping away. You don't need to feel badly about it. If you are interested, though, in continuing, even if it is at a slow pace for now, I'm also ok with that. I have a new post-doc starting sometime this summer who is interested in some of these issues. If you decide to stay on, it's possible that you could shift your role at that point to a more conceptual one and he would take on more of the detailed data analysis and modeling. I'm not sure what he's going to end up working on, so I guess what I'm really saying is that if I find someone to take on more of the project, you could still stay involved (pretty much in the way I am currently).

Let me know what you decide.

BTW, how are things going there? How do you like life as a faculty member?

Best,
Dave
A unifying account of visual motion and position perception

Oh-Sang Kwon¹, Duje Tadin¹ and David C. Knill¹,#

Kwon, Tadin, Knill, PNAS, in press
Fig. 1. Schematic illustration of the object tracking model and its behavior. A, An example of an object with...

Kwon, Tadin, Knill, PNAS, in press
- motion-induced shifts in perceived position
- peripheral slowing
- curveball illusion
"Dave was my postdoctoral mentor. He was brilliant yet strict in research, but generous in life. It was always enlightening to have a meeting with him. He could see through to the core of my vague ideas, which I might have been thinking about for weeks. Usually before my full description finished, he would come up with several better ones in mathematically organized form. I adored his ability. He encouraged me to explore fundamental principles governing human behaviors rather than to search for eye-catching effects, while urging every bit of research to be crystal clear. I am greatly indebted to him."

Oh-Sang Kwon  
(postdoc 2009-2014)

Talk 21.14, tomorrow morning
Rochester, Feb 2011

Liu, Knill, Kersten 1995

![Diagram showing probability distribution for orientations, with two classes: Class 1 and Class 2.](image)
Portland, 2012
VSS 2014