Human-machine interaction in virtual reality

Paul MacNeilage, Psychology

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VR Research Topics?

- Interfaces – locomotion, manipulation, eye movements
- Other modalities – haptics, audio, etc.
- Adaptation – advantages, disadvantages
- Sickness – conflict, methods to reduce it
- Presence – methods to increase it

Experiments on Human Subjects

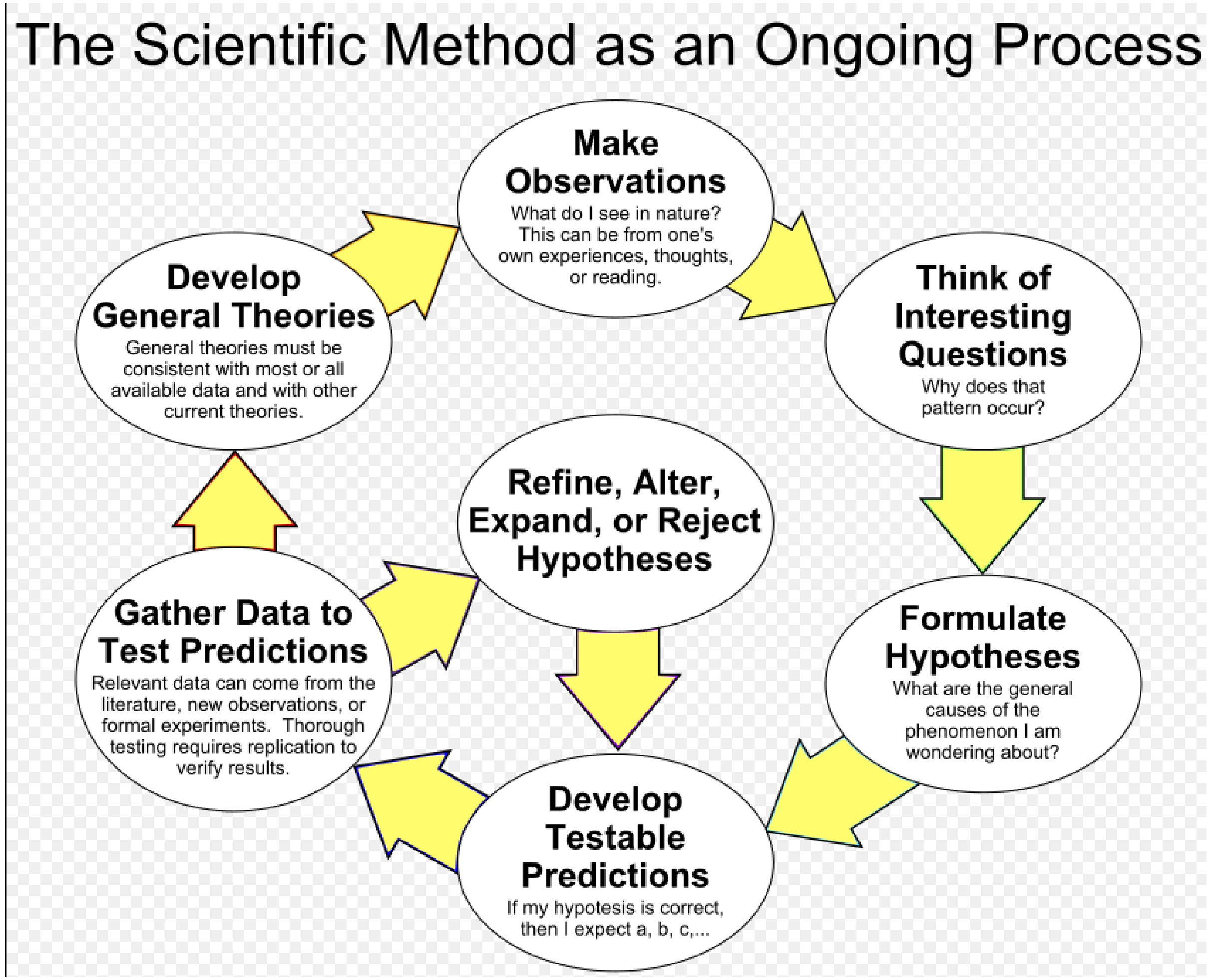
- Central to VR research and development
- Necessary to prove that a novel method, technology, practice is really beneficial
- All claims should be scientifically proven
- Don’t trust introspection!

Experimental psychology

Human factors research

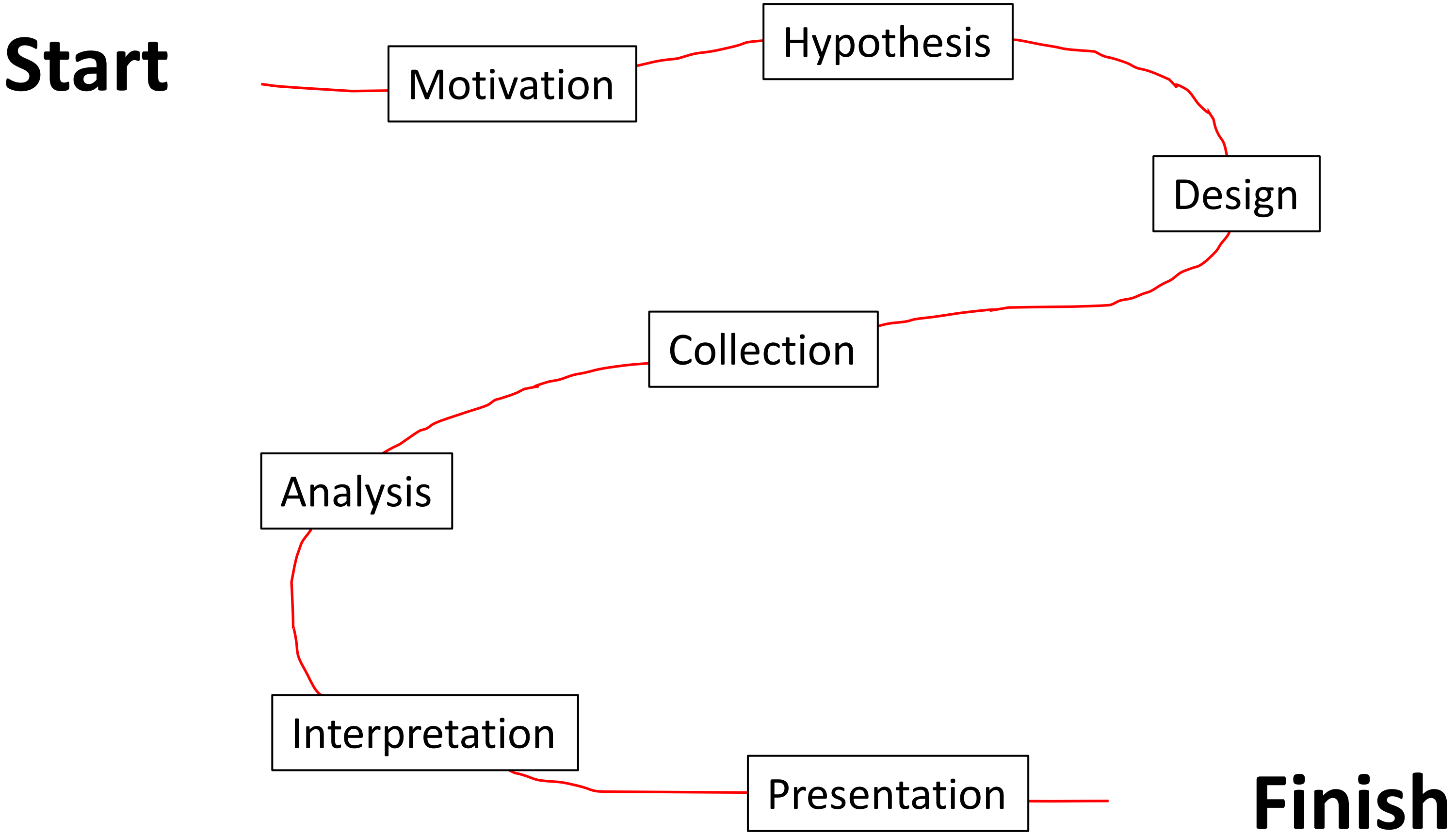
Human-computer interaction

Scientific Method



From Wikipedia

Experimental Process



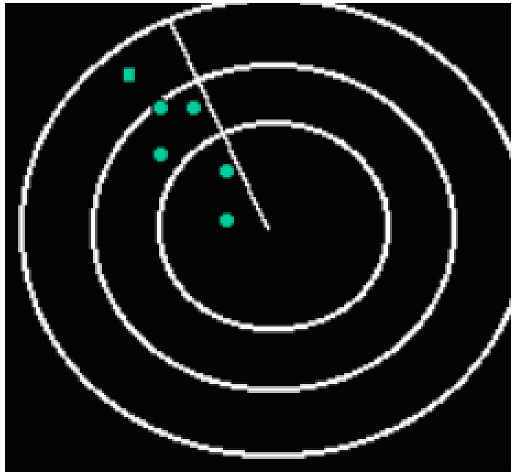
Psychophysics

- Measuring a psychometric function
- Multisensory interactions
  - Cue integration
  - Conflict detection

- Related to textbook sections:
  - Chapter 12.4: Experiments on human subjects
  - Chapter 6.4: Combining sources of information
  - Chapter 8.4: Mismatched motion and vection

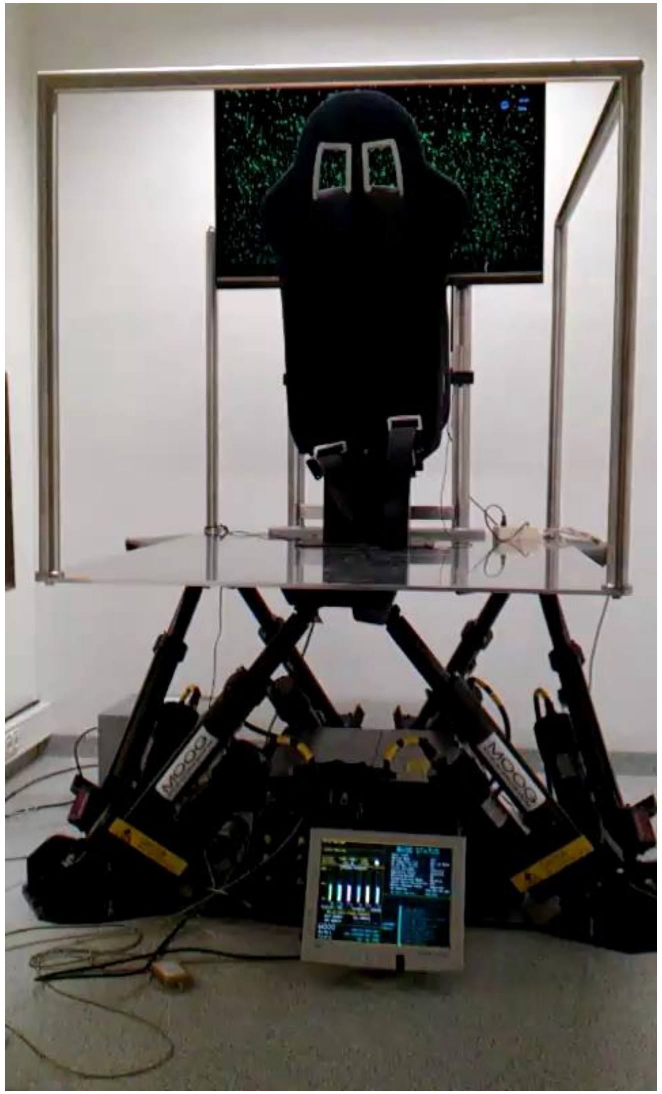
Signal Detection Theory

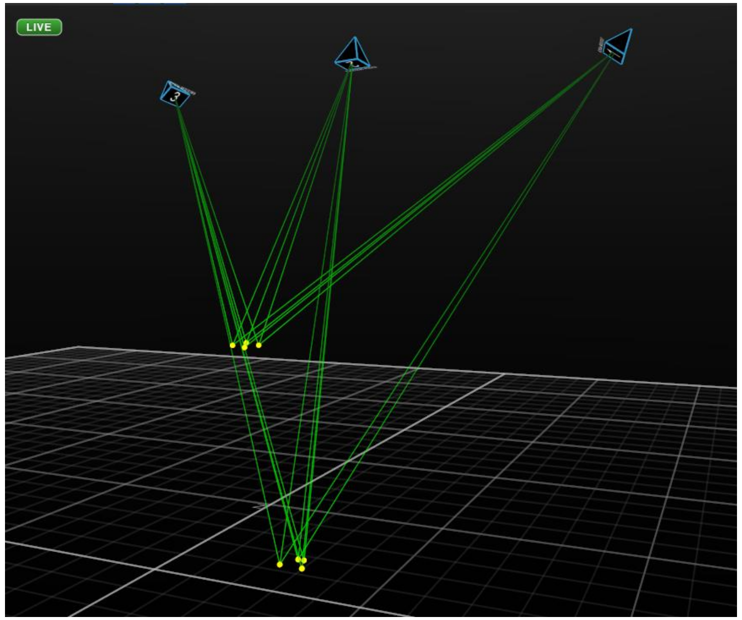
- Mathematical model for decision-making in the face of uncertainty
- Ability to tell signal from noise
- Originally developed during WWII to interpret radar readings

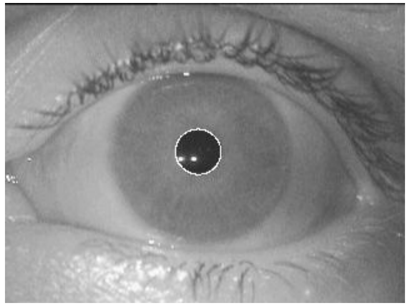


- Later applied to psychological research

Self-motion Lab

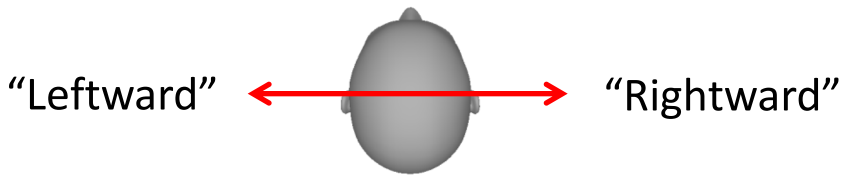


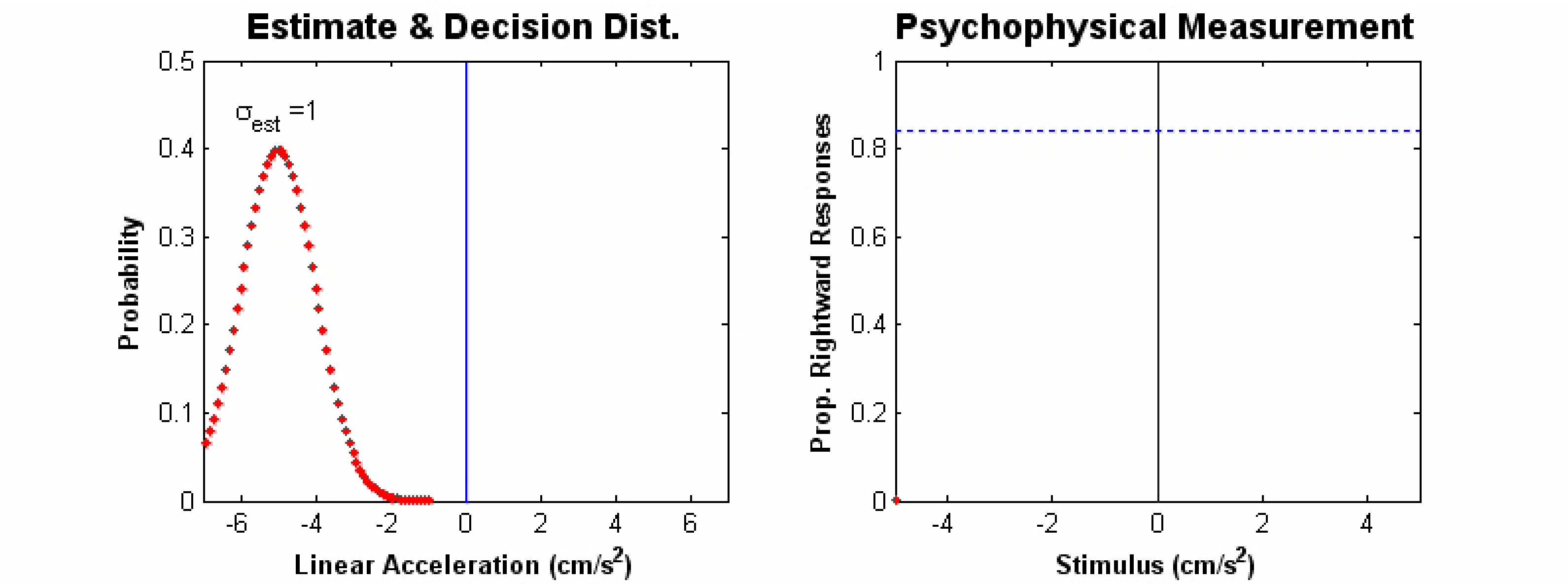




Vestibular Perceptual Sensitivity

One-interval forced choice procedure

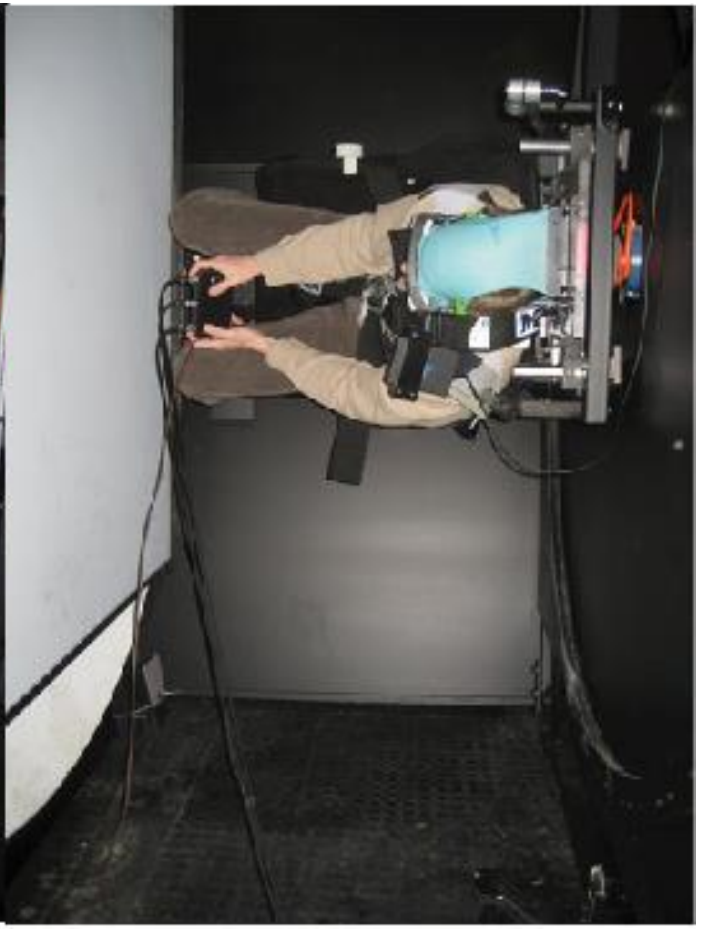




MacNeilage, Banks, DeAngelis, Angelaki 2010

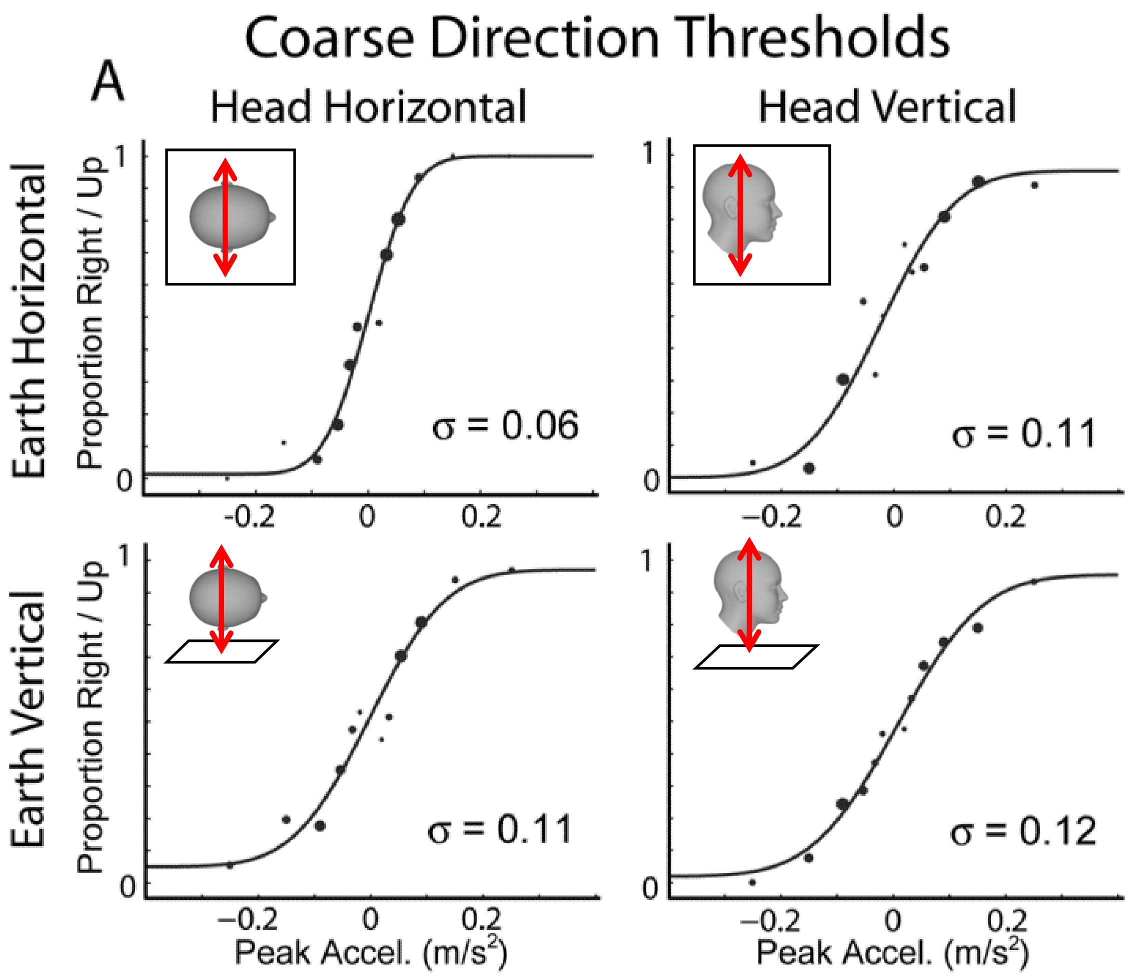
Motion platform and chair

Upright



Side-down

Vestibular Perceptual Sensitivity



MacNeilage, Banks, DeAngelis, Angelaki 2010

Relevance for VR

- Rigorous methods for quantifying perception
- May be applied in almost any context
  - Vision: depth, motion, color, etc.
  - Audition: loudness, pitch, location, etc.
  - Haptic: size, shape, etc.
  - Multisensory:
    - Cue integration
    - Conflict detection

Today's topics

- Measuring perception: psychophysics
- Multisensory interactions
  - Cue integration
  - Conflict detection

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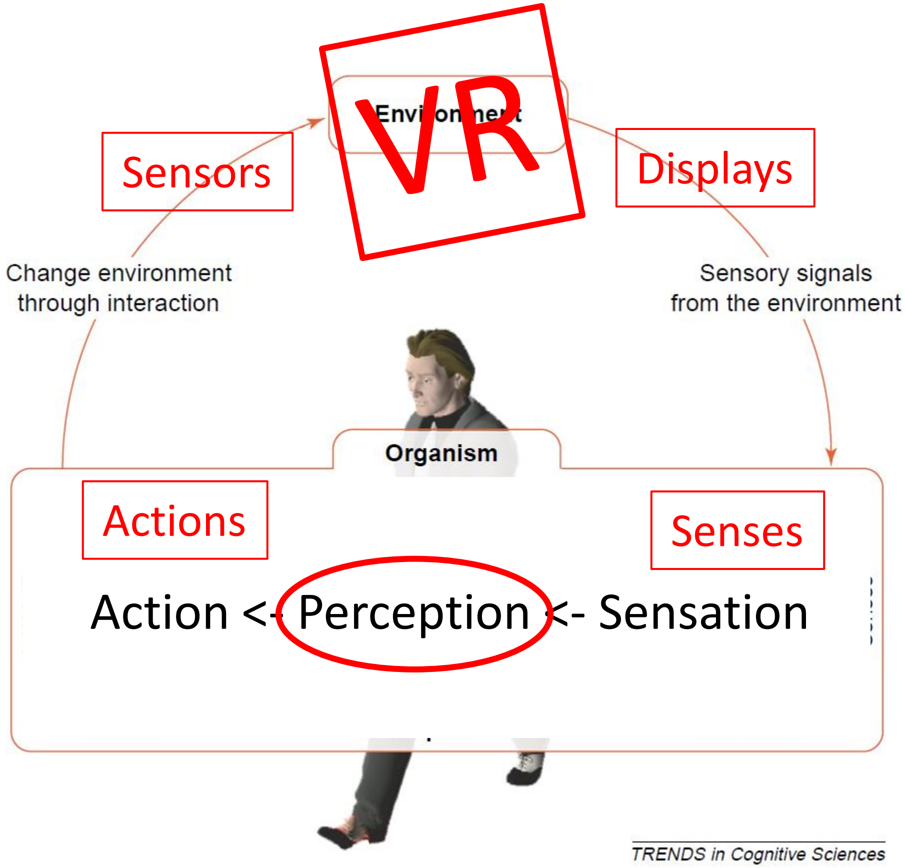
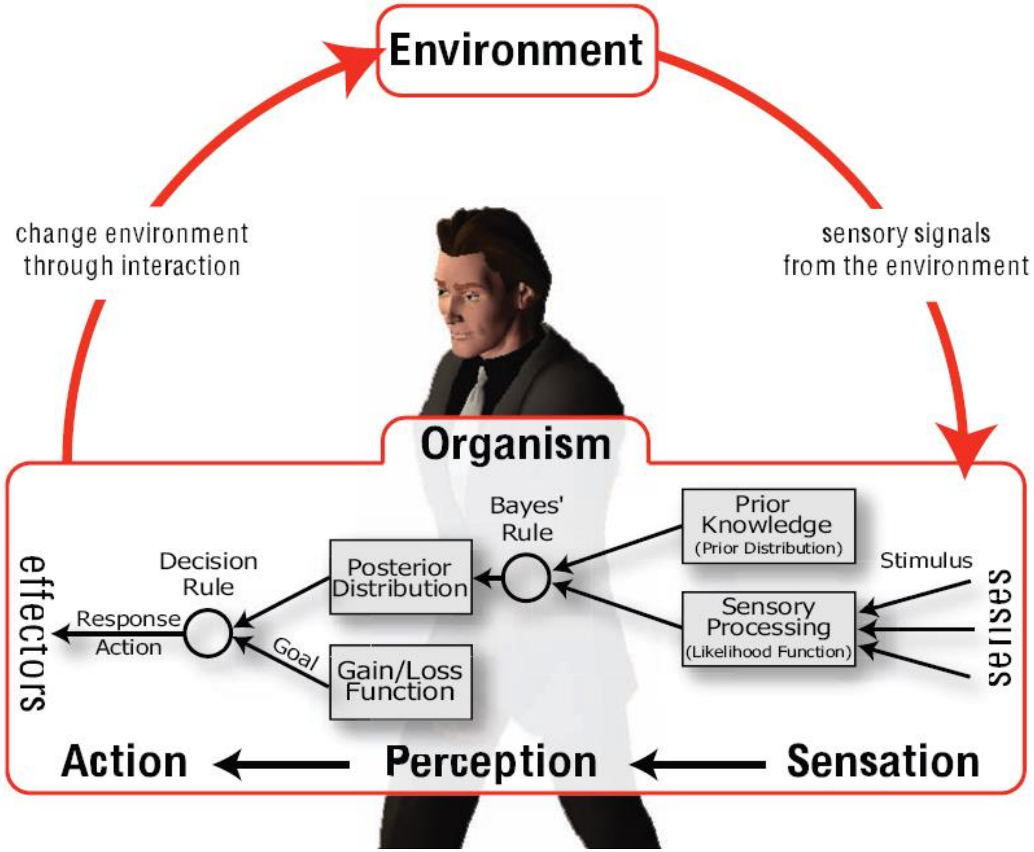
Human-VR Loop



Ernst & Bulthoff 2004

Perception as Bayesian Inference

- Brain must infer the state of the outside world from incomplete information



Ernst & DeLuca 2011

Probabilistic Framework

- Sensory information = evidence (I)

- Physical states = possible interpretations (S)

- What is the most likely interpretation given the available evidence? $P(S|I)$

Bayes' rule / law / theorem

- Mathematical description of the problem

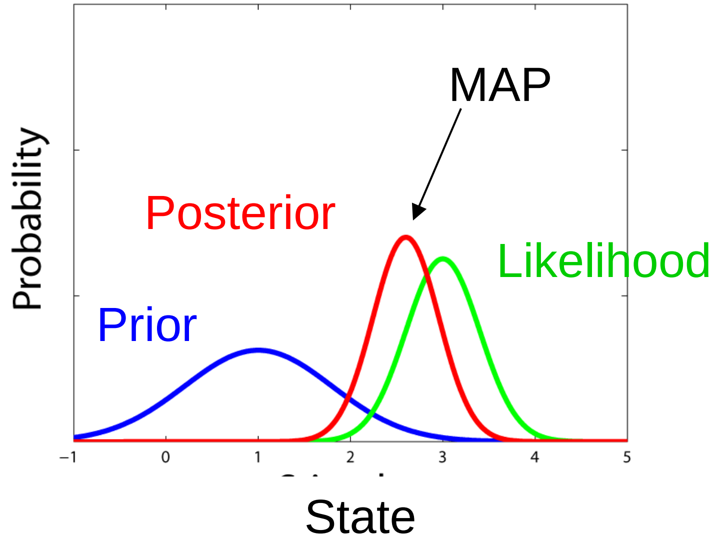
$$P(S \mid I) \propto P(I \mid S)P(S)$$

<u>Posterior</u>	<u>Likelihood</u>	<u>Prior</u>
used to make perceptual judgment	sensory information	knowledge, experience

Bayes' rule / law / theorem

- Mathematical description of the problem

$$P(S \mid I) \propto P(I \mid S)P(S)$$



- Decision rule: maximum a posteriori (MAP)

Priors Responsible for Many Illusions

- Light-from-above prior

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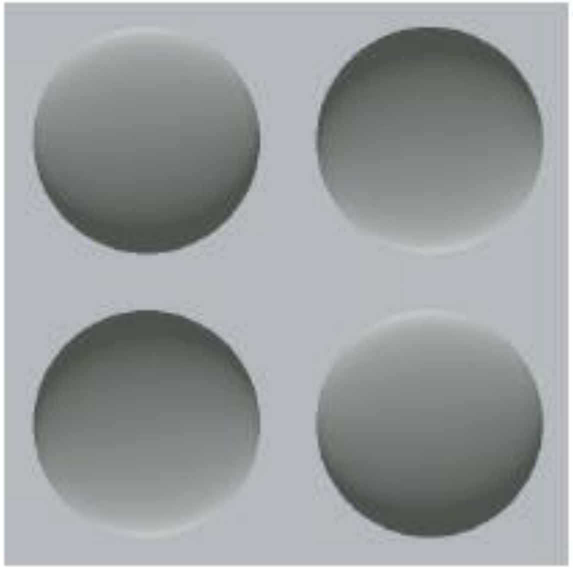


Cue Integration

- How does the brain combine different sources of information?
- According to the rules of probability!
- Bayes rule can be applied

Perception Depends on Many Cues

- Example: multiple visual cues to distance

Perception Depends on Many Cues

- Example: visual and haptic cues to size

Visual

Haptic

- Different senses referred to as modalities

Maximum-likelihood Estimation (MLE)

- Bayesian Model of Cue Combination
- Assumptions:
  - Gaussian Noise (i.e. normally distributed)
  - Independence
  - Uniform prior

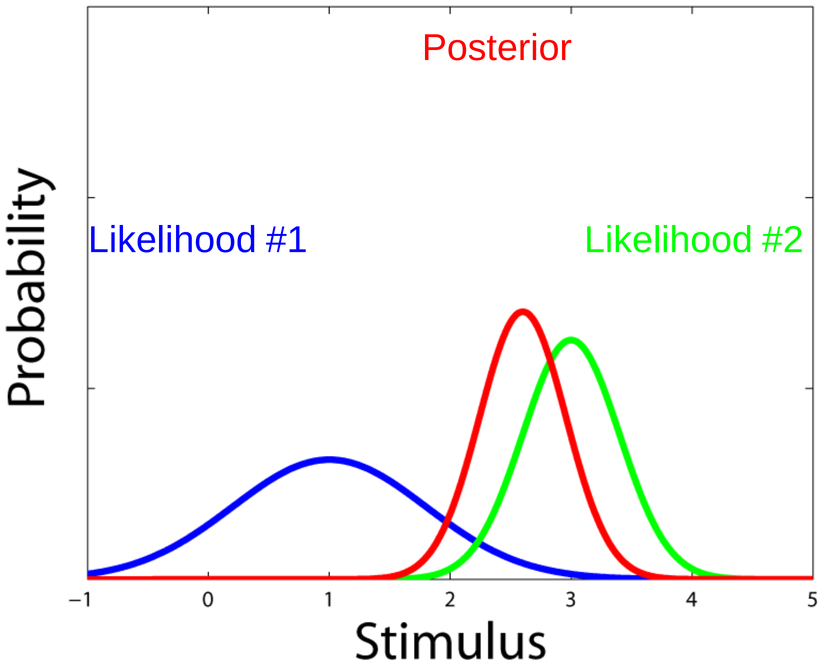
$$P(S \mid I_1, I_2) \propto P(I_1 \mid S) P(I_2 \mid S)$$

Maximum-likelihood Estimation (MLE)

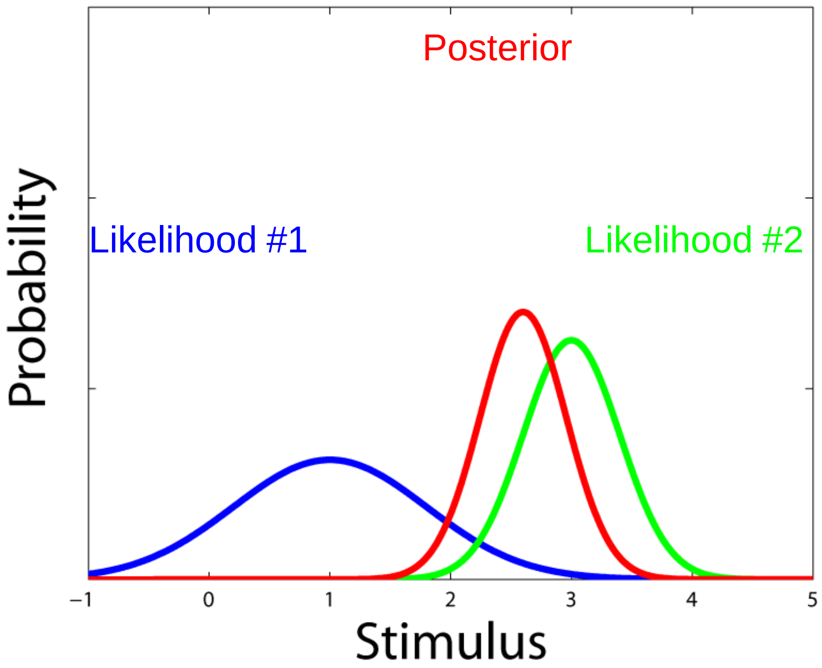
- “Optimal” estimate is weighted linear combination of contributing cues

- Weights determined by relative cue reliabilities

- Combined estimate is less variable than any cue in isolation



Maximum-likelihood Estimation (MLE)



Predictions

1) Weight depends on relative variability

$$\boxed{\hat{S}_{comb} = \hat{S}_1 w_1 + \hat{S}_2 w_2}$$

$$\boxed{w_1 + w_2 = 1}$$

$$\boxed{w_i = \frac{1}{\sigma_i^2} \Big/ \sum_{j=1}^{n} \frac{1}{\sigma_j^2}}$$

2) Combined estimate is least variable

$$\boxed{\sigma^2{}_{comb} = \frac{\sigma^2{}_1 \sigma^2{}_2}{\sigma^2{}_1 + \sigma^2{}_2}}$$

Humans integrate visual and haptic information in a statistically optimal fashion

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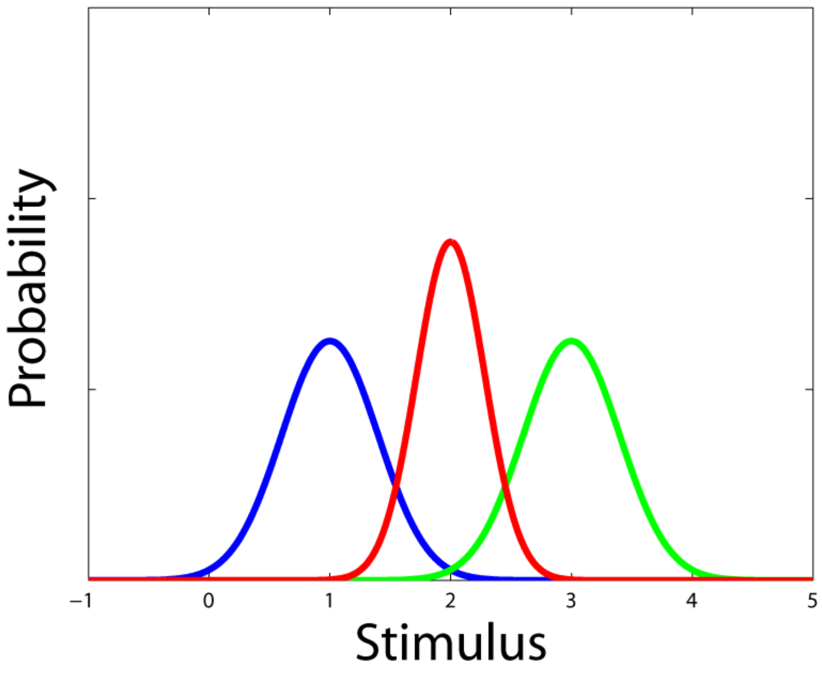
Vision Science Program/School of Optometry, University of California, Berkeley 94720-2020, USA

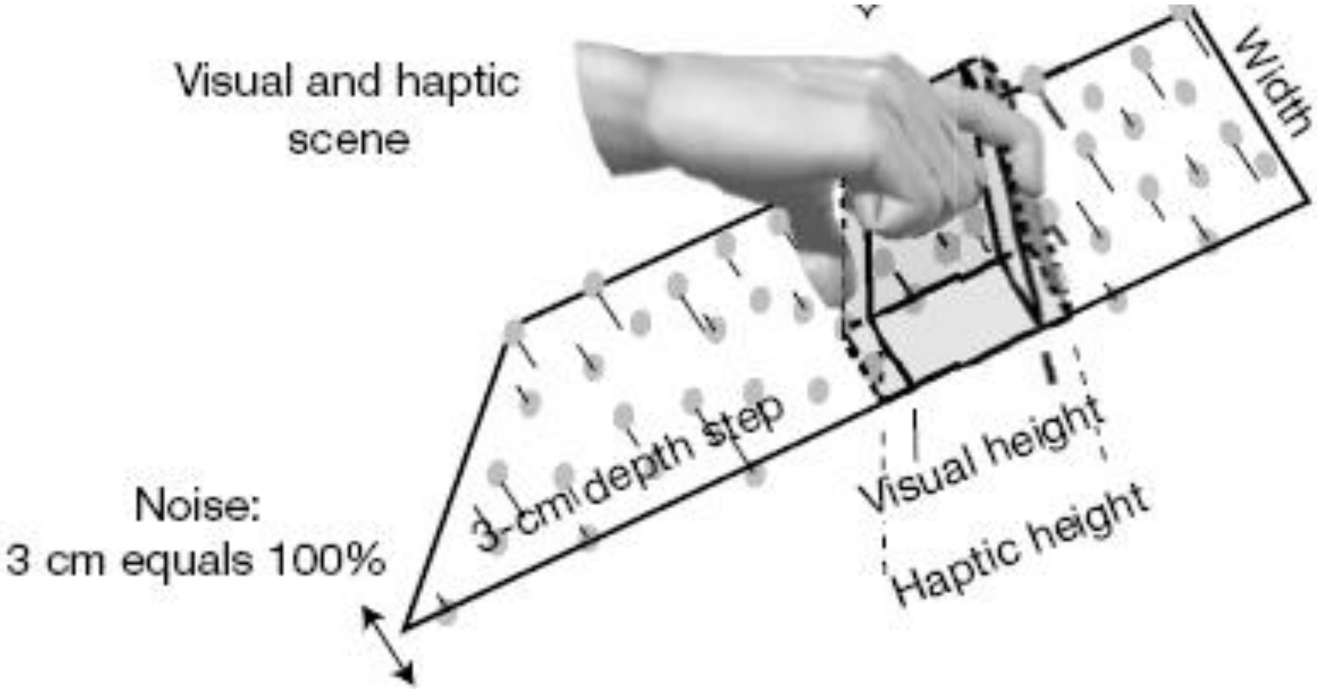
When a person looks at an object while exploring it with their hand, vision and touch both provide information for estimating the properties of the object. Vision frequently dominates the integrated visual–haptic percept, for example when judging size, shape or position[1–3], but in some circumstances the percept is clearly affected by haptics[4–7]. Here we propose that a general principle, which minimizes variance in the final estimate, determines the degree to which vision or haptics dominates. This principle is realized by using maximum-likelihood estimation[8–15] to combine the inputs. To investigate cue combination quantitatively, we first measured the variances associated with visual and haptic estimation of height. We then used these measurements to construct a maximum-likelihood integrator. This model behaved very similarly to humans in a visual–haptic task. Thus, the nervous system seems to combine visual and haptic information in a fashion that is similar to a maximum-likelihood integrator. Visual dominance occurs when the variance associated with visual estimation is lower than that associated with haptic estimation.

Conditions

- Visual-only
- Haptic-only
- Combined



Psychophysical Task

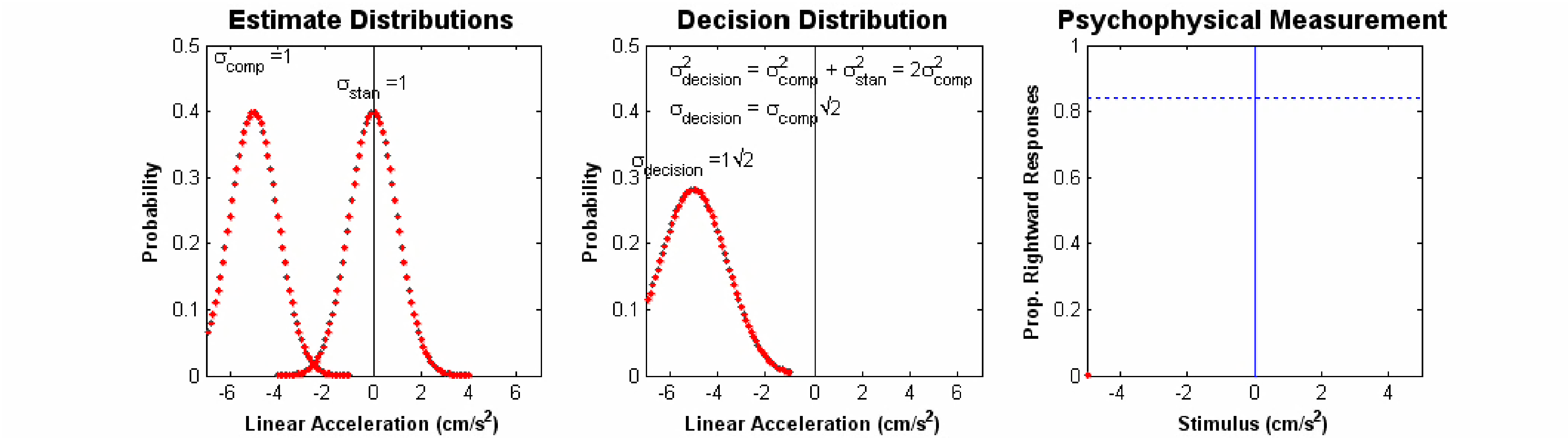


- 2-Interval-Forced-Choice

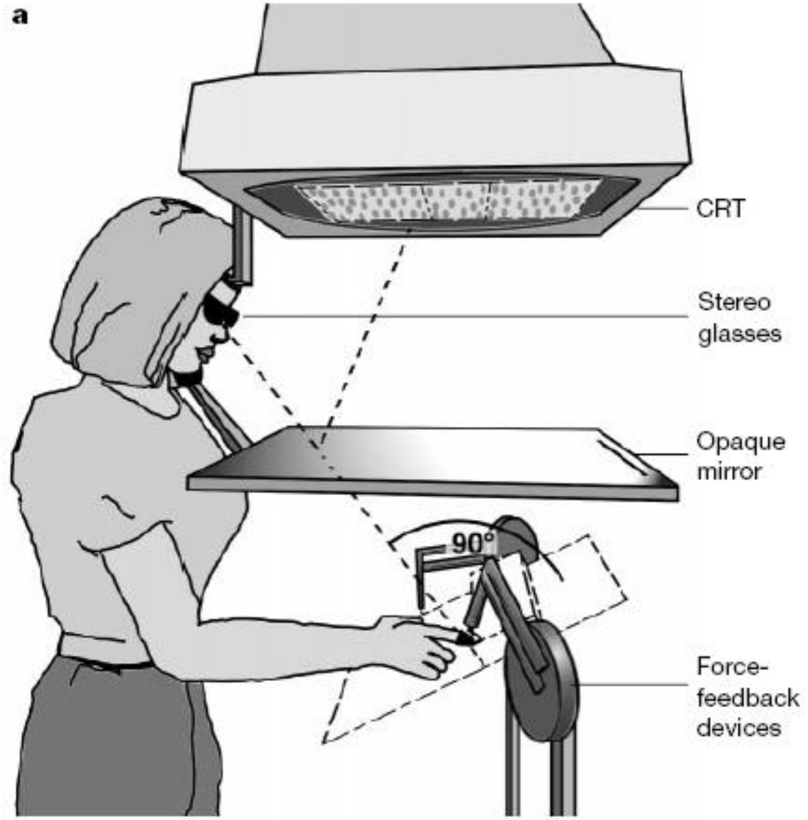
  “Which bar was bigger?”

SDT: Two-interval forced choice

- "Which bar was bigger?"

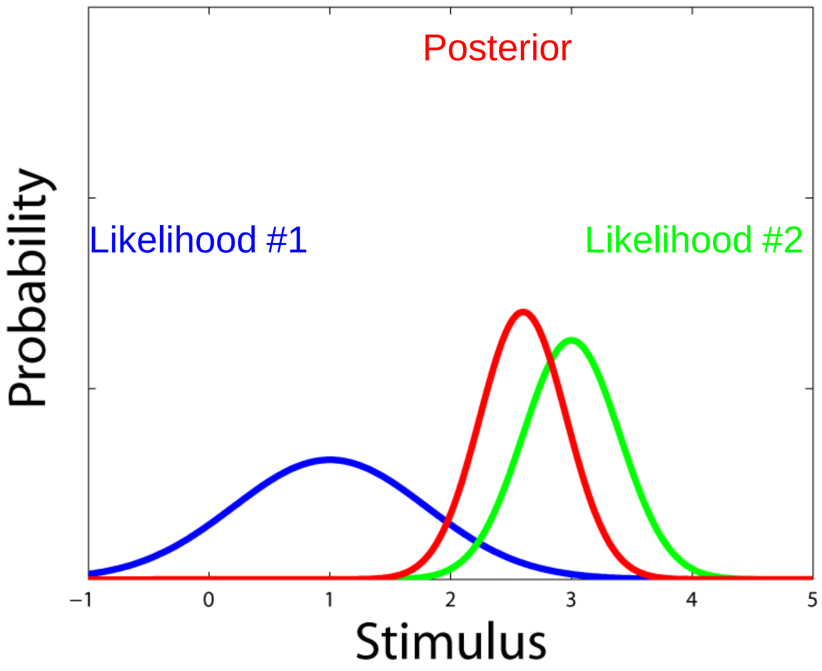


Haptic VR Equipment



- “Phantom” force-feedback device

Maximum-likelihood Estimation (MLE)



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2) Combined estimate is least variable

$$\boxed{\sigma^2{}_{comb} = \frac{\sigma^2{}_1 \sigma^2{}_2}{\sigma^2{}_1 + \sigma^2{}_2}}$$

Additional Examples of MLE

- Disparity & texture cues to surface slant (Knill 1998)
- Visual & proprioceptive cues to location (van Beers et al 1999)
- Visual & auditory cues to location (Gharamani et al. 1998)
- Visual & vestibular cue to heading(Butler et al 2010)
- Et cetera…

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Self-motion Lab

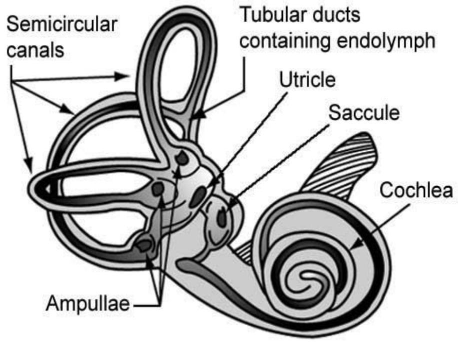
Sensory and Motor Signals Mediating Stationarity Perception

Dr. Paul R. MacNeilage

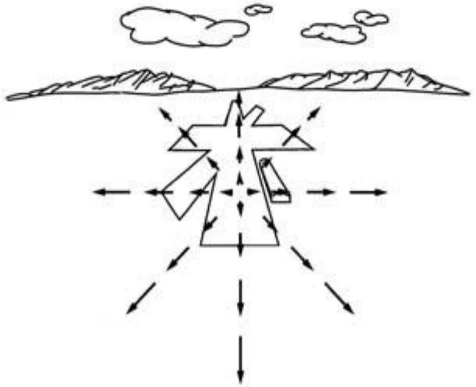
Department of Psychology and Institute for Neuroscience

University of Nevada, Reno

Vestibular

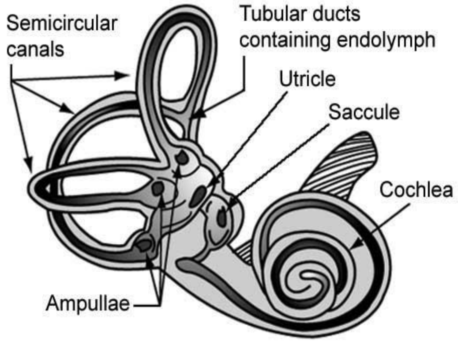


Visual



Stationarity Perception

Vestibular



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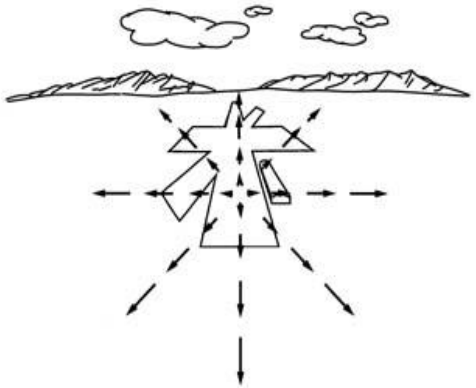
Visual



Perception of a stable world

Stationarity Perception

- Allows vision to be used for self-motion estimation
- Deficits of stationarity perception are debilitating
  - Disorientation, imbalance, vertigo, sickness
- Underlies effective virtual/augmented reality technology

Outline

- Signal detection model of stationarity perception
- Psychophysical measurement of stationarity perception
- Factors impacting stationarity perception
  - Motor signals
    - Oculomotor signals
    - Cephalomotor signals
  - Visual stimulus parameters
    - Spatial frequency
    - Retinal stimulus location
- Relation between stationarity perception and sickness

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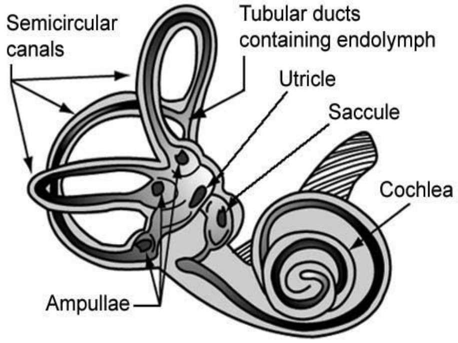
Congruence Evaluation

- Are visual and non-visual self-motion signals congruent?

Vestibular



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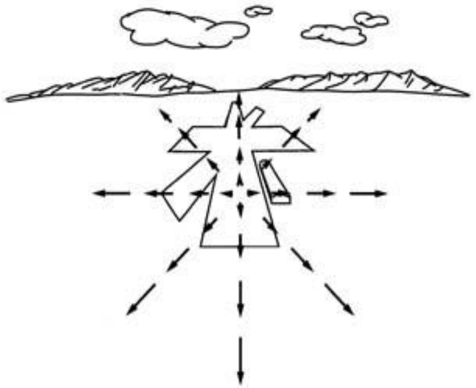
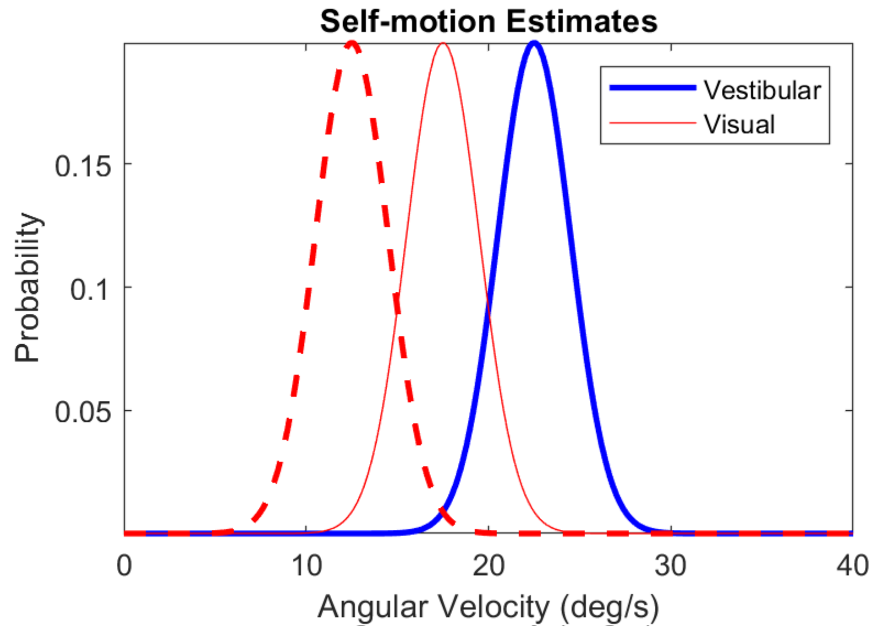
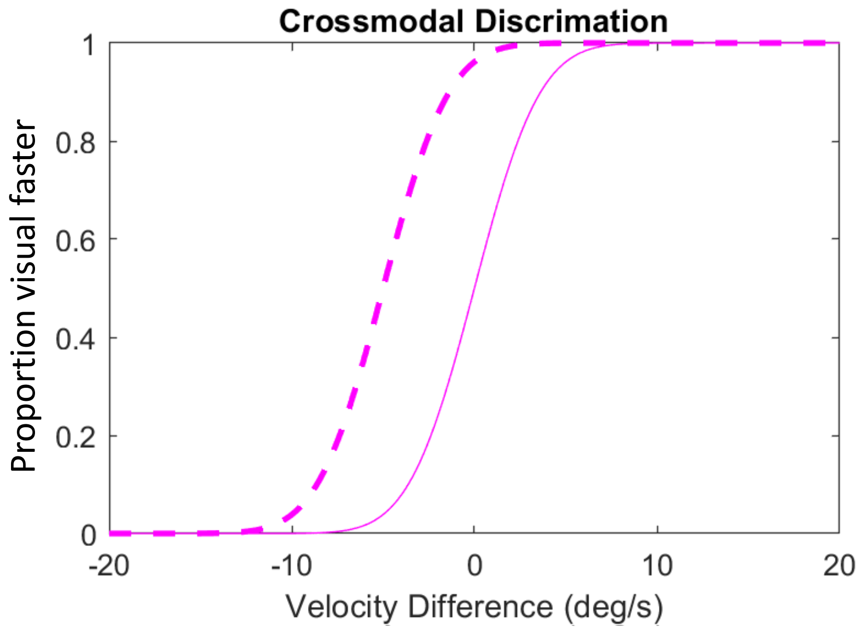
Visual



Crossmodal Discrimination Model

- How does the nervous system evaluate congruence in support of stationarity perception?





- What factors impact self-motion and crossmodal discrimination?

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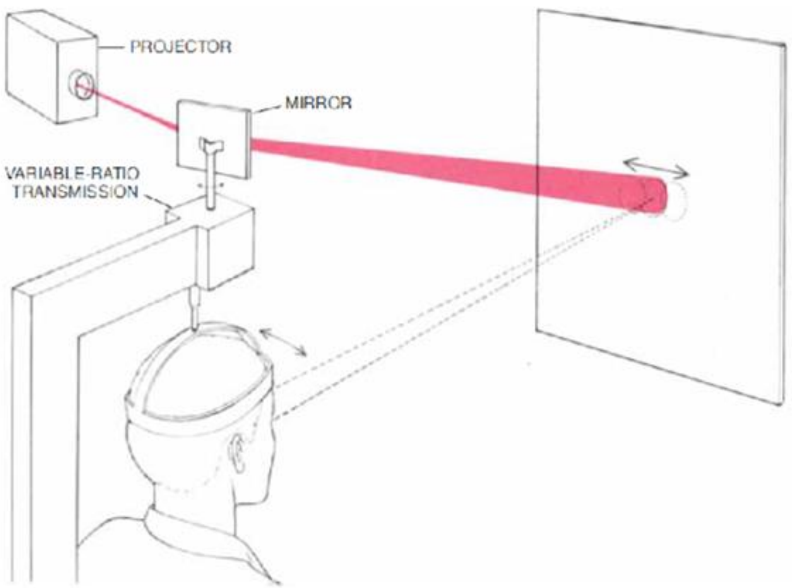
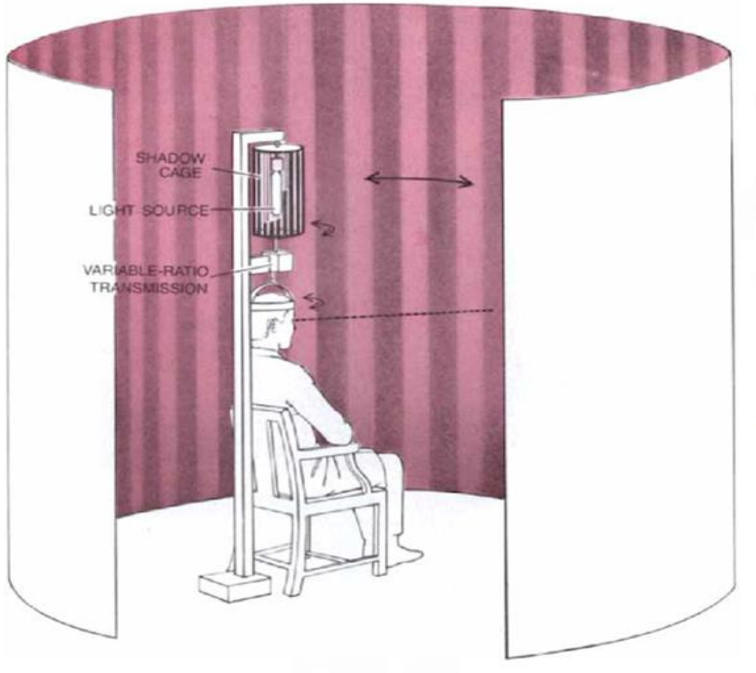
Stationarity Perception Paradigm - Analog





"Range of Immobility"

Wallach & Kravitz (1965)

Stationarity Perception Paradigm - Hybrid

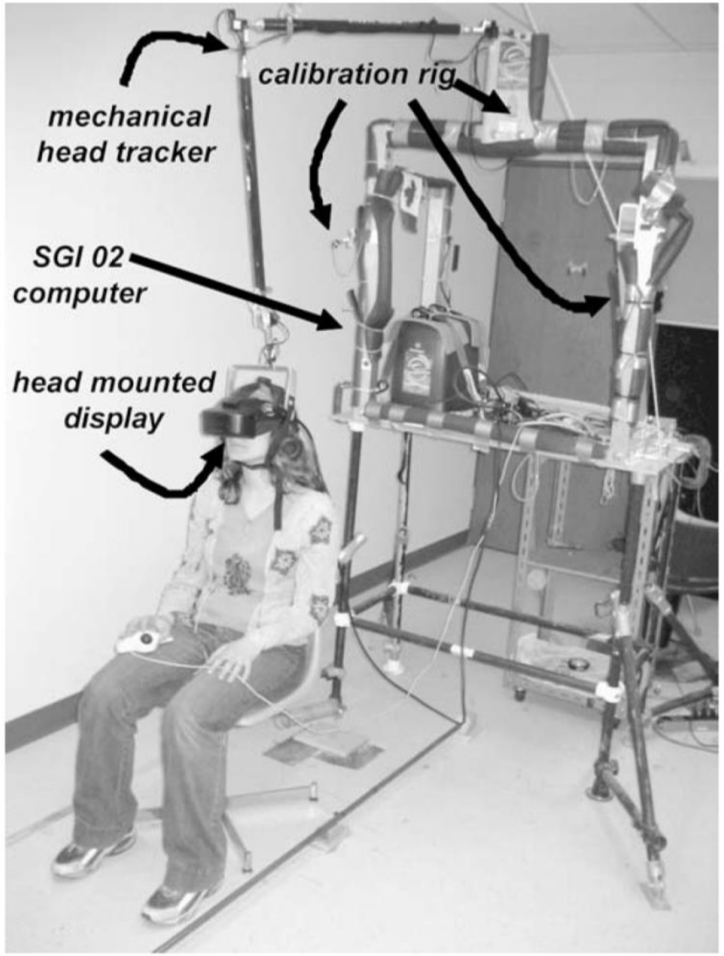
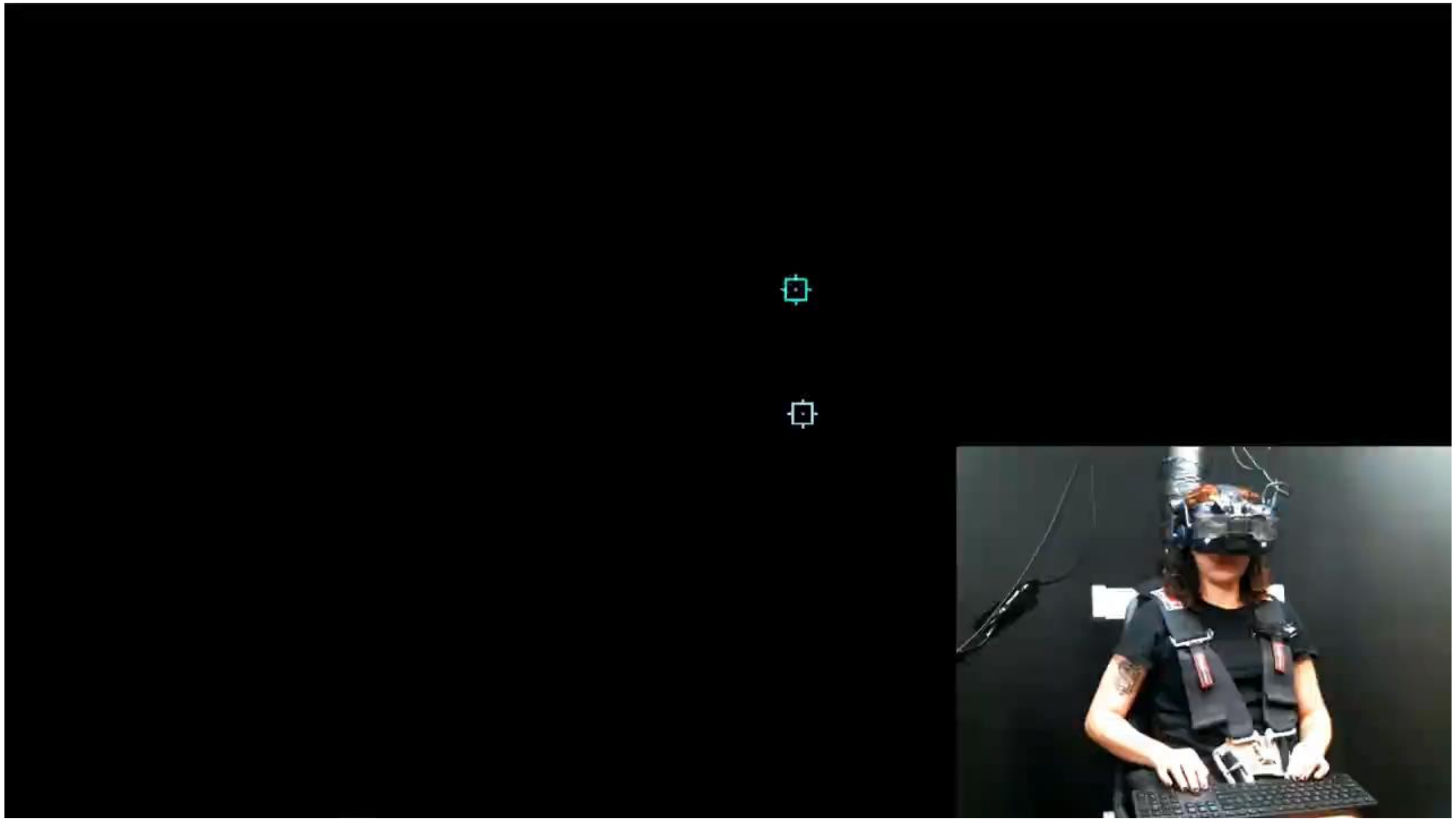


Fig. 1 Experimental setup. A Puppetworks mechanical head tracker was used to track head position while subjects viewed a virtual sphere in a Virtual V8 head mounted display. The simulation was run by an SGI 02 computer

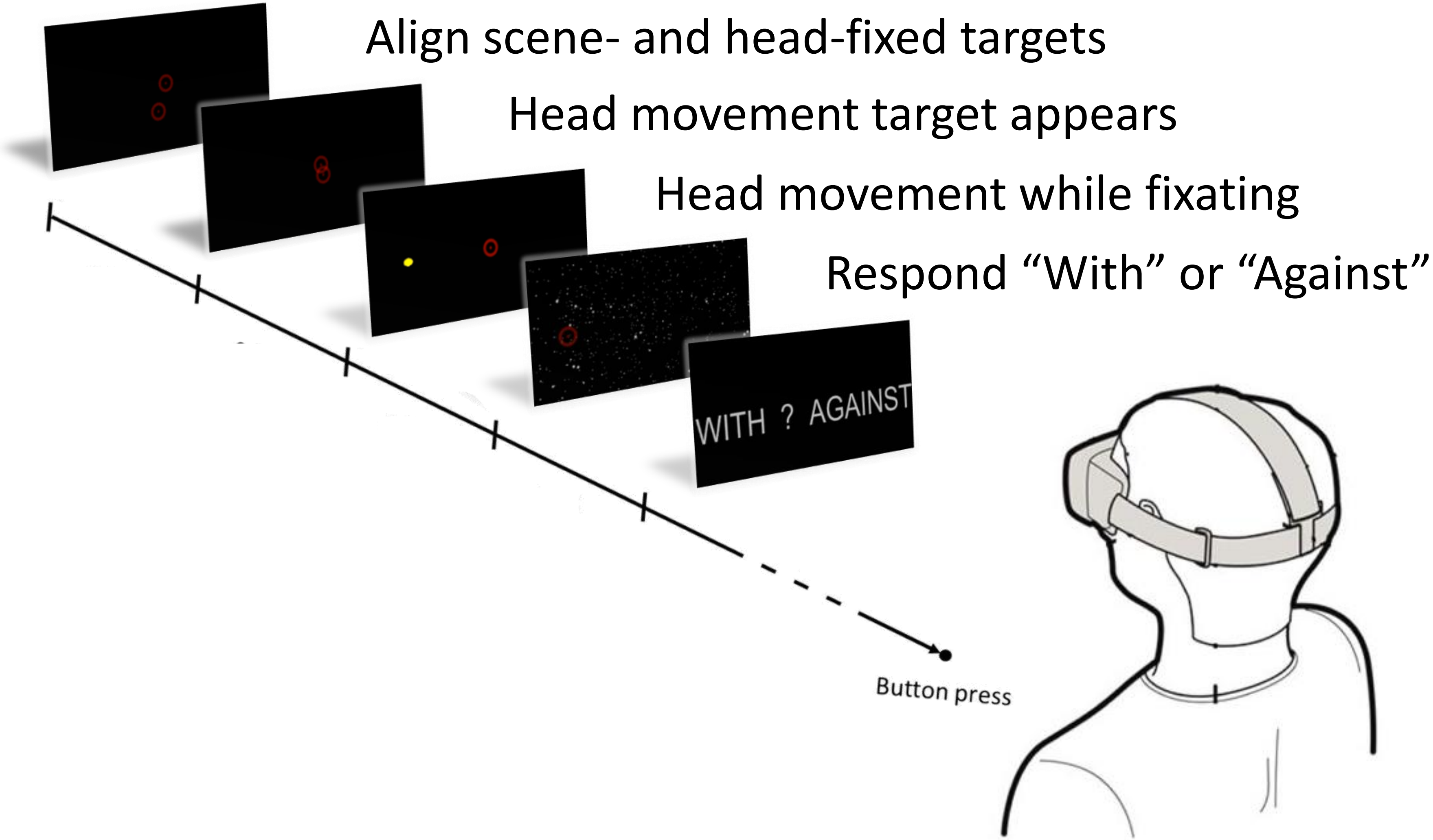
- Rotation:
  - Roll, pitch, yaw
- Translation:
  - Naso-occipital, interaural, dorsoventral

Jaekl et al (2002, 2005)

Stationarity Perception Paradigm - Digital

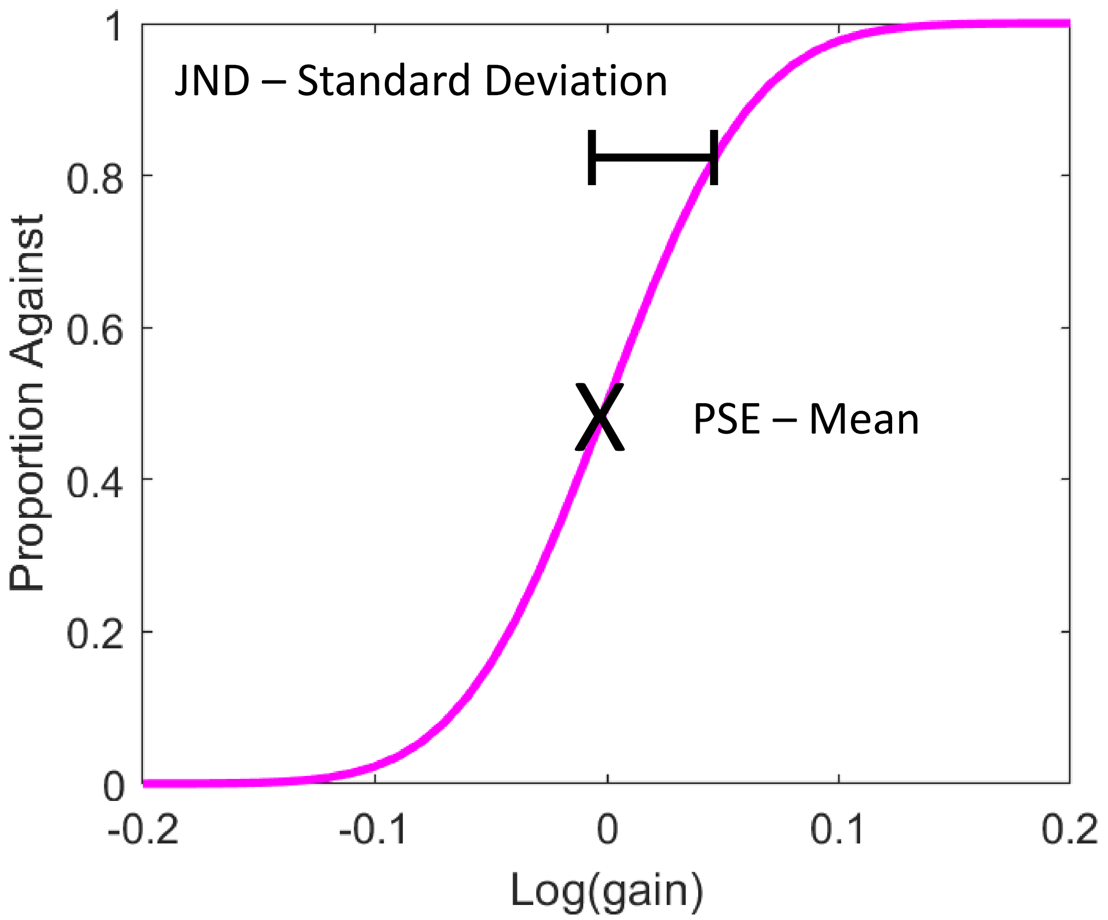


2AFC Procedure



Accuracy and Precision of Stationarity Judgments

- Accuracy
  - PSE – point of subjective equality
  - Visual gain perceived stationary
- Precision
  - JND – just-noticeable difference
  - Range of immobility/stationarity



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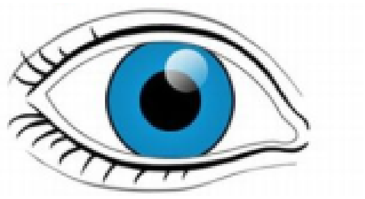
Role of oculomotor signals

Oculomotor



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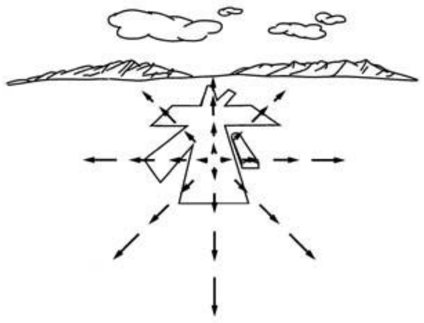
Retinal Flow



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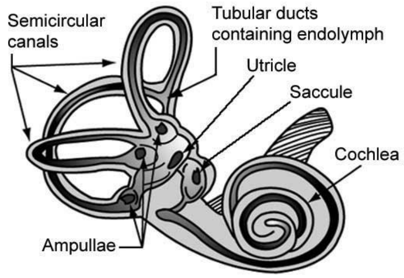
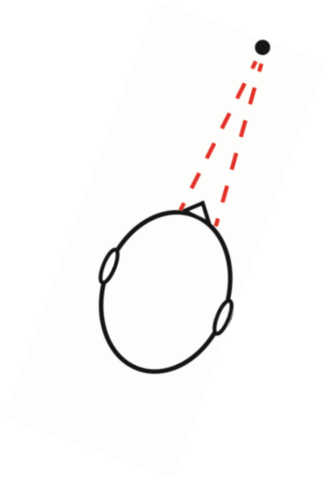
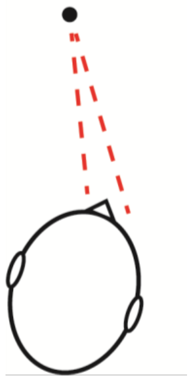
Vestibular



Head-fixed fixation

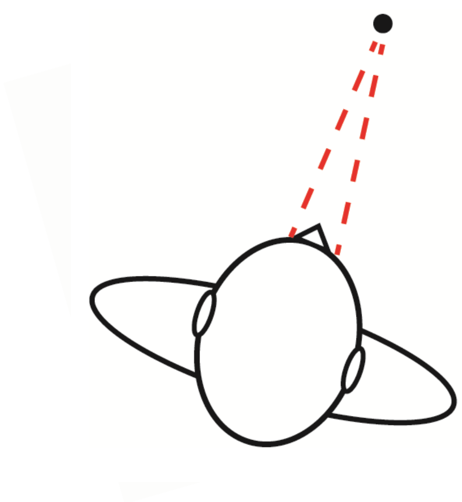


Scene-fixed fixation

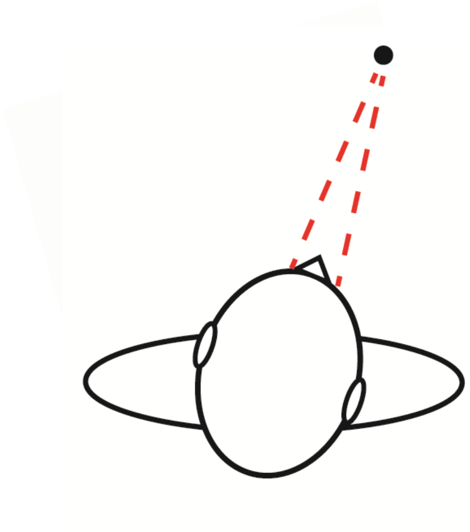


Role of cephalomotor signals

Passive

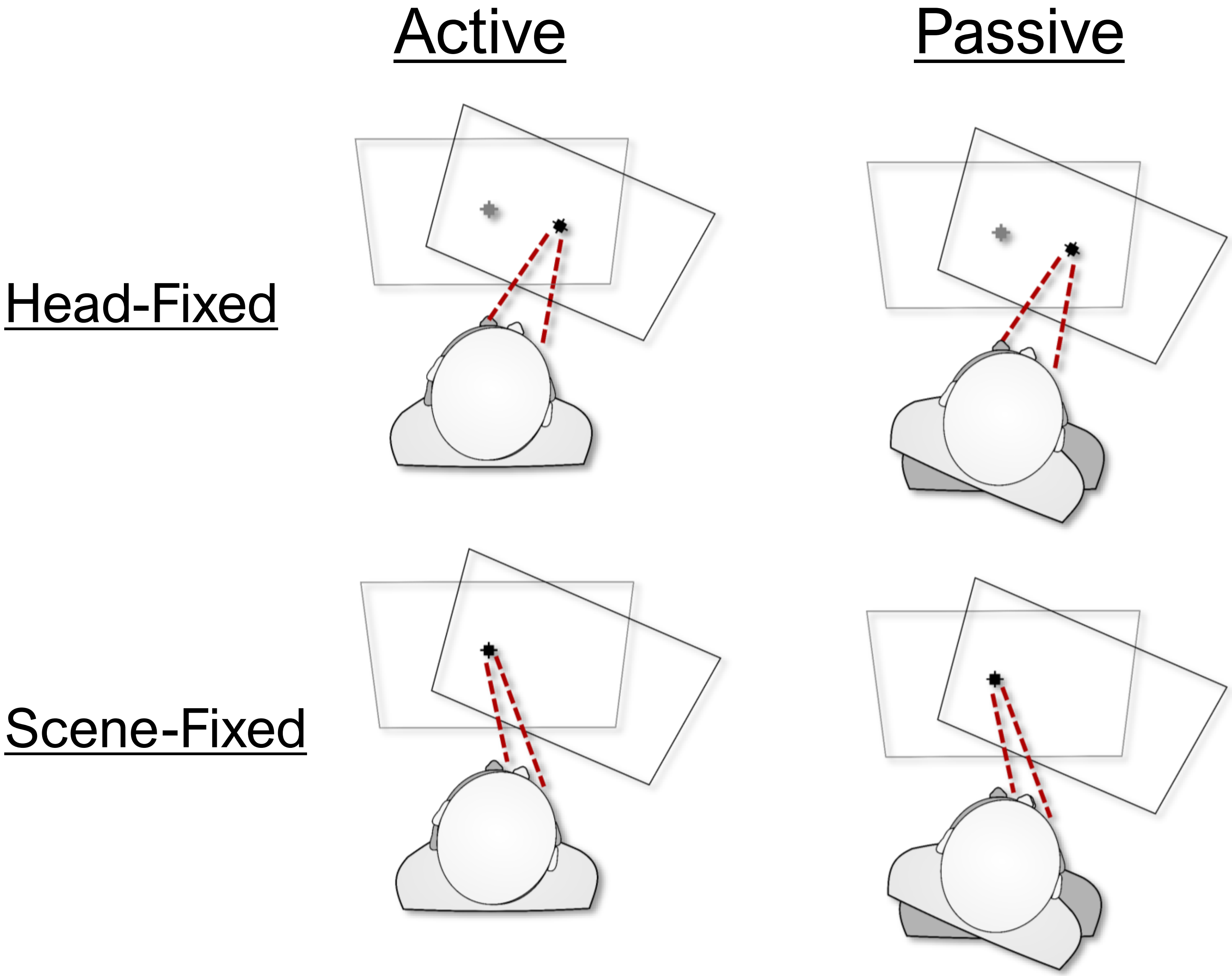


Active

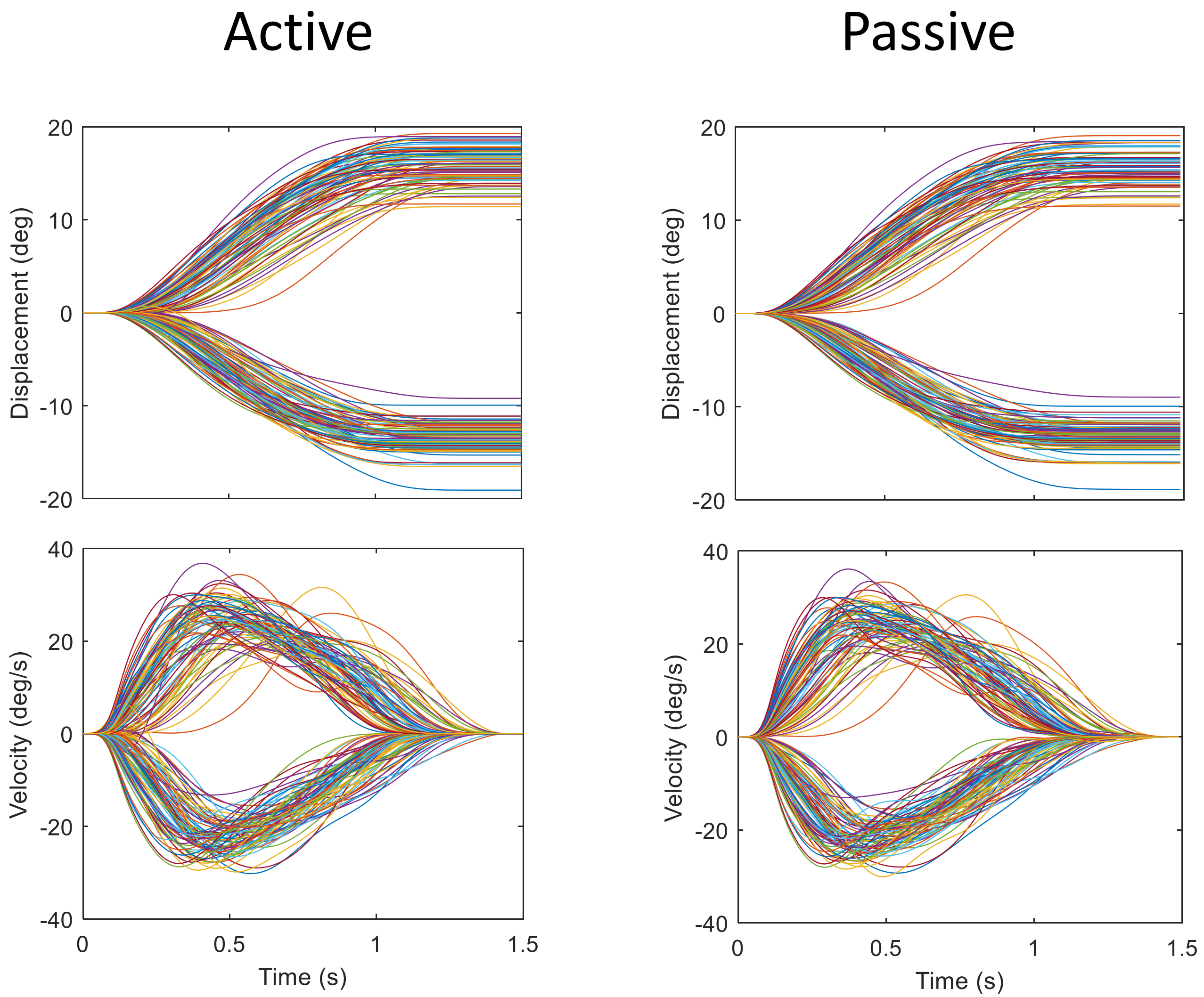


Movement Conditions

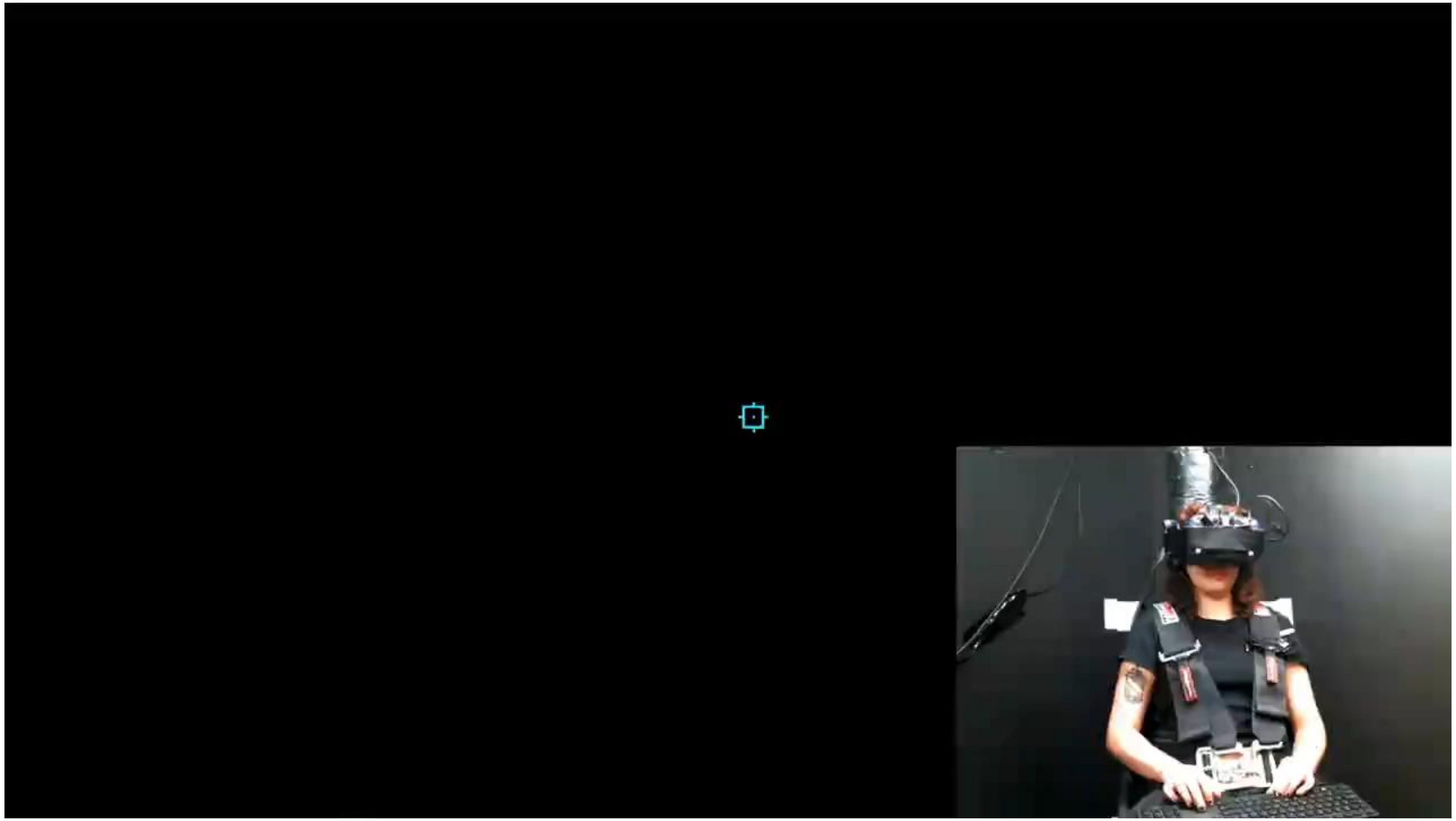
- Adaptive staircase
  - 150 trials per condition
- 20 subjects
- Visual scene – dot cloud



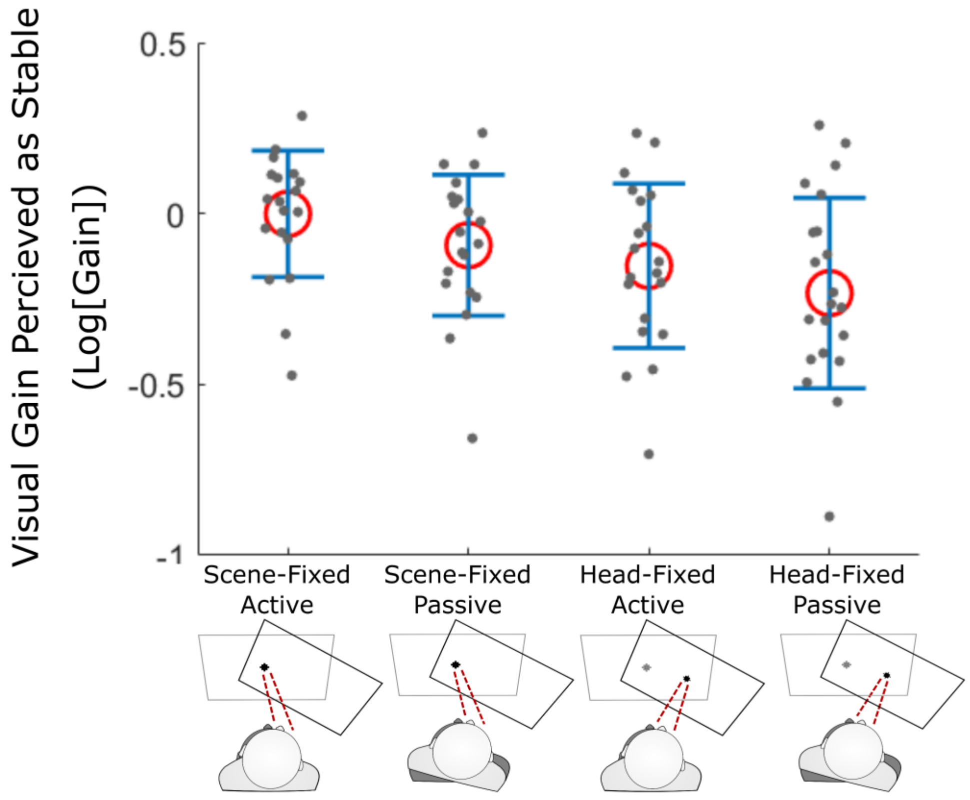
Passive playback of active trajectories

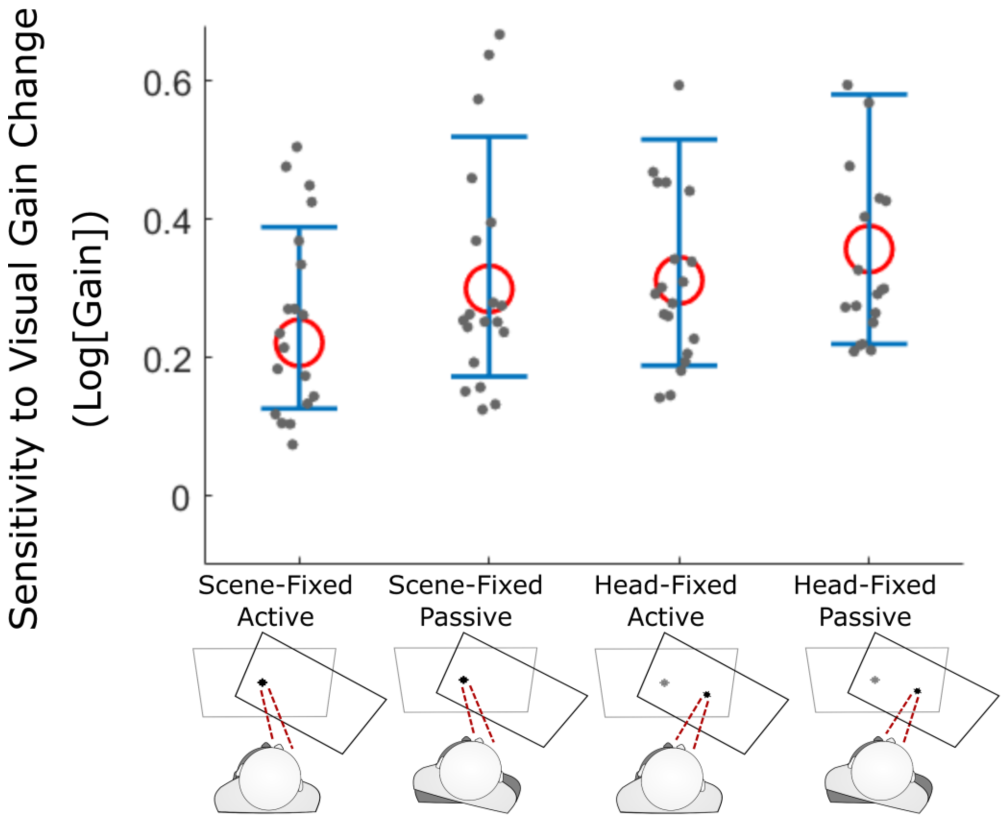


Passive playback of active trajectories



PSEs and JNDs





Motor signals associated with naturalistic eye and head movement facilitate conflict detection.

Active vs passive head movement

- Reduced gain during passive head movement
  - Underestimation of head movement
- Reduced sensitivity during passive movement
  - Increased noise because motor signals are absent
- Consistent with spatial updating
  - Mergner et al (1998)
  - Genzel et al (2016)

Scene- vs head-fixed fixation

- Reduced gain during head-fixed fixation
  - Underestimation of head movement (Clemens et al. 2017)
  - Overestimation of visual scene motion (Garzorz et al 2018)

- Reduced sensitivity during head-fixed fixation
  - Increased signal-dependent noise on retinal image motion? (Garzorz & MacNeilage 2017)

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Spatial frequency

- Speed perception increases with spatial frequency (Diener et al 1976)
- Oculomotor responses may also depend on spatial frequency
- How does stationarity perception depend on spatial frequency?

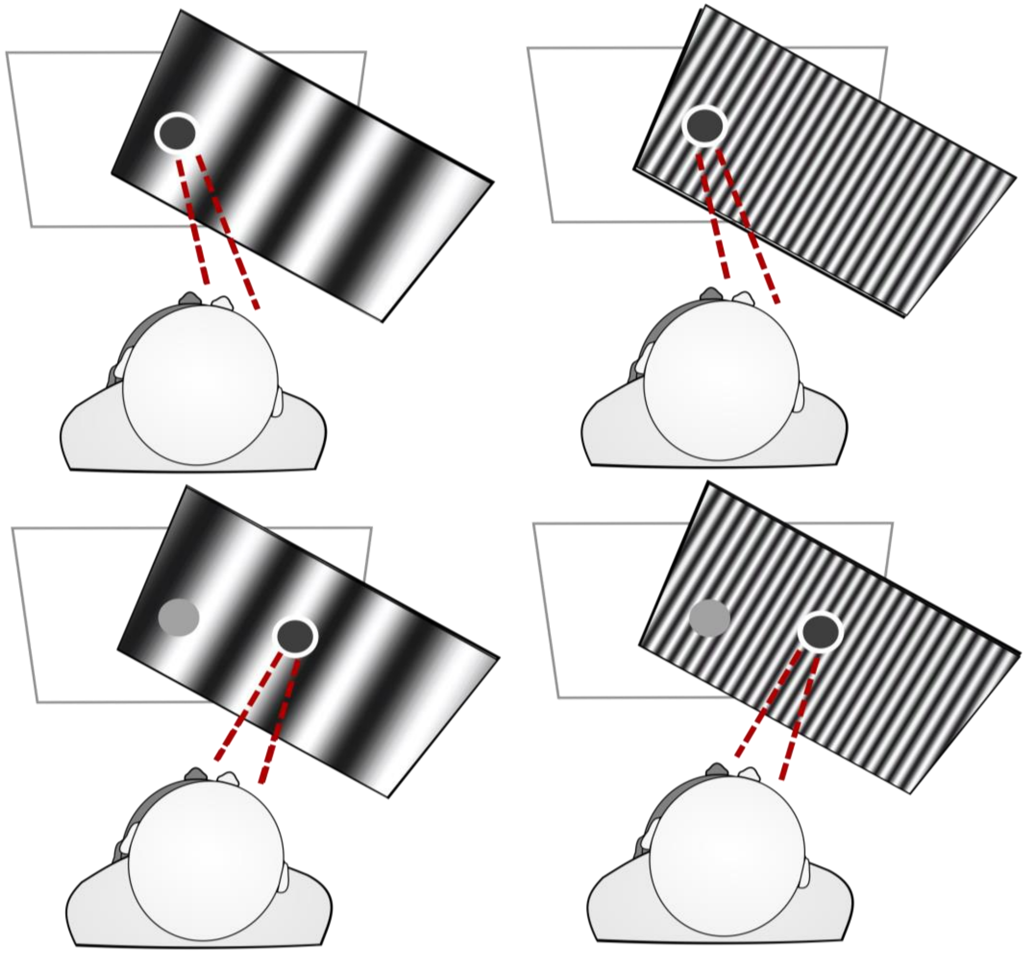
Conditions

- Adaptive staircase
  - 300 trials per condition
- 19 subjects

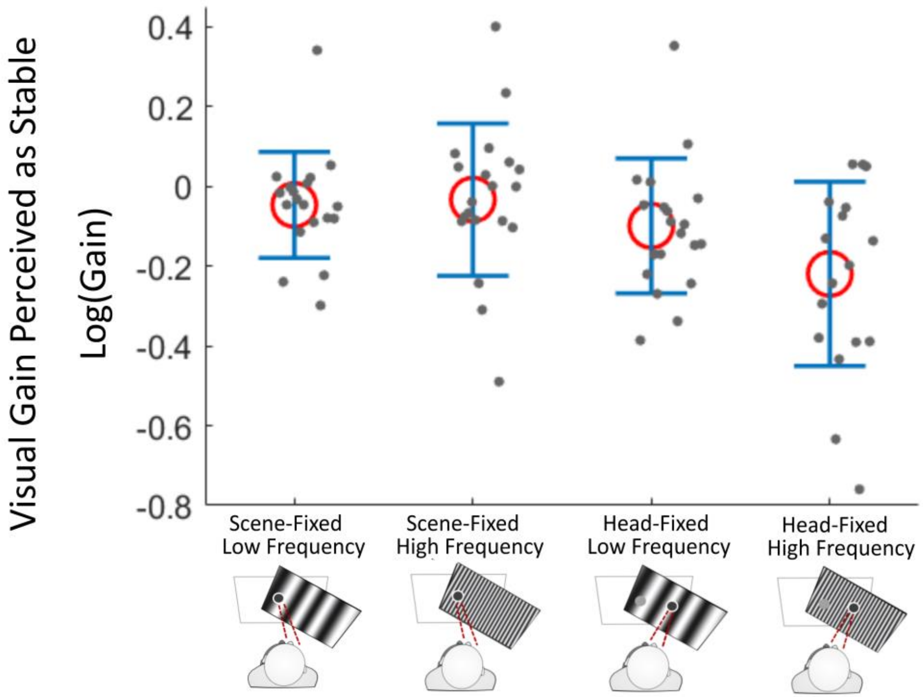
Low SF (0.2 cpd) High SF (2 cpd)

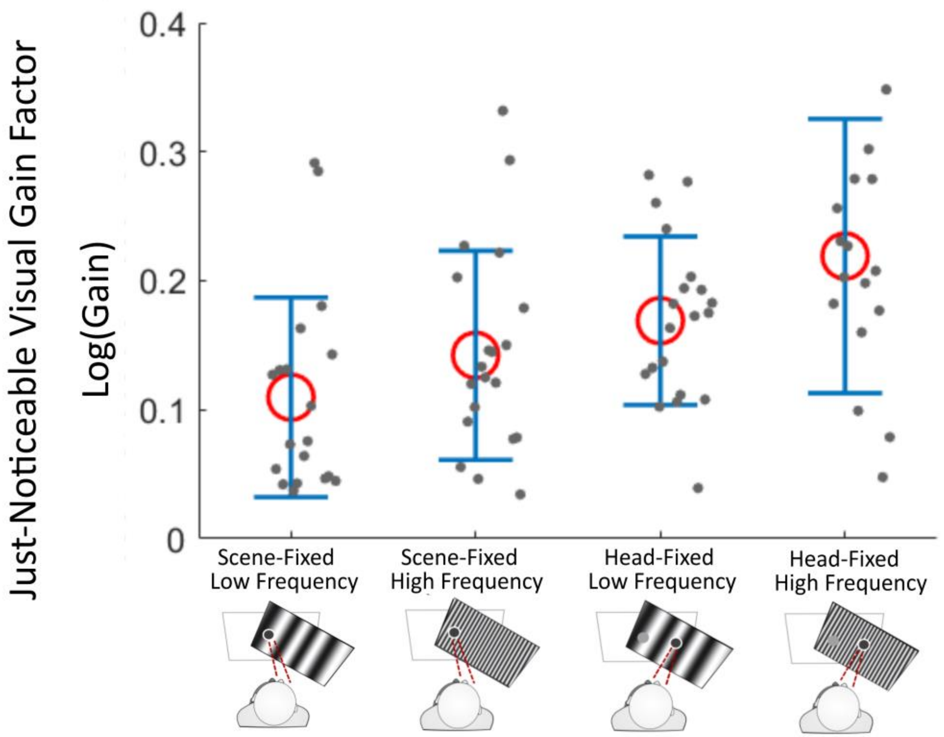
Scene-fixed

Head-fixed



PSEs and JNDs





More accurate and precise with lower spatial frequency.

Spatial frequency effects

- More accurate with low spatial frequency
  - High frequencies may lead to overestimation of speed
  - Self-motion estimation may favor low spatial frequency channels
- More precise with low spatial frequency
  - Higher spatial frequencies lead to noisier speed estimates
- These effects are most pronounced during head-fixed fixation
  - Retinal speed estimation depends more on spatial frequency than oculomotor

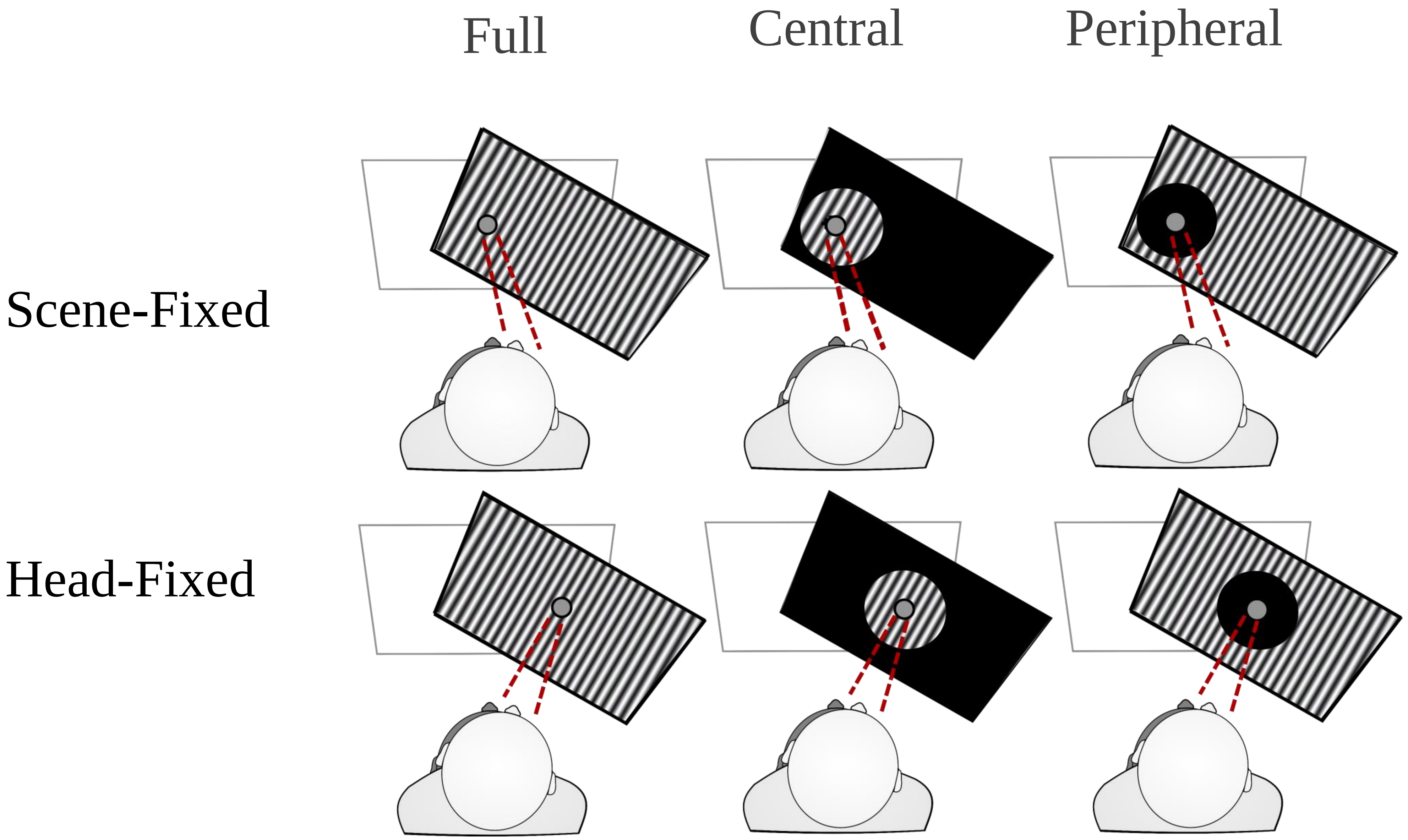
Outline

- Signal detection model of stationarity perception
- Psychophysical measurement of stationarity perception
- Factors impacting stationarity perception
  - Motor signals
    - Oculomotor signals
    - Cephalomotor signals
  - Visual stimulus parameters
    - Spatial frequency
    - Retinal stimulus location
- Relation between stationarity perception and sickness

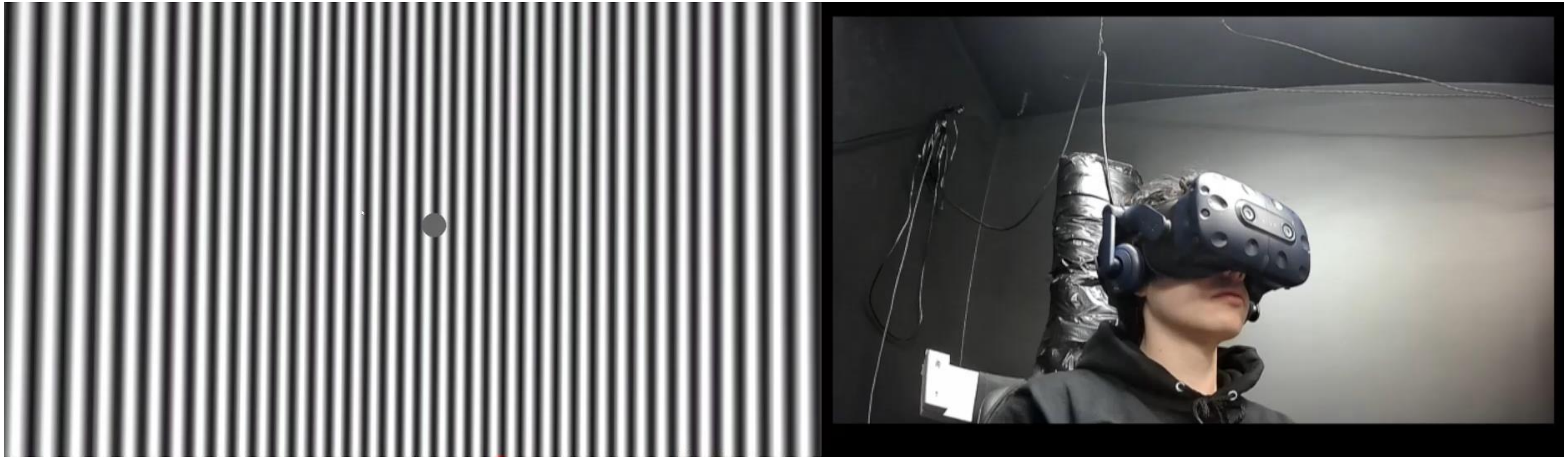
Visual motion processing varies with eccentricity

- Motion processing varies with retinal eccentricity
- Vection is driven strongly by peripheral stimulation (Brandt et al 1973)
- How is motion integrated across the visual field to drive stationarity perception?

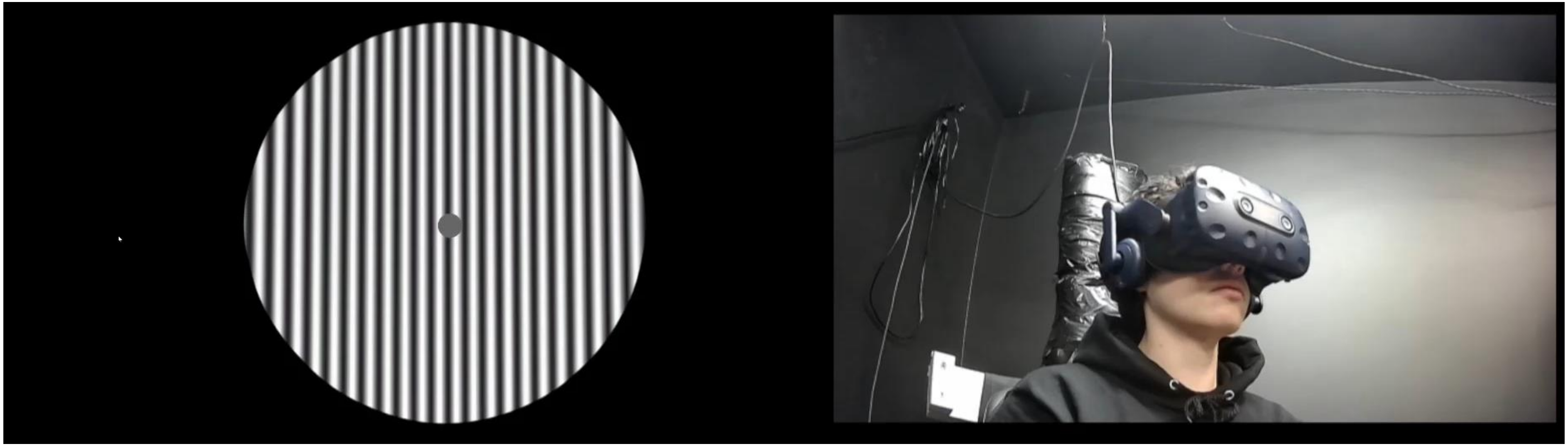
Conditions



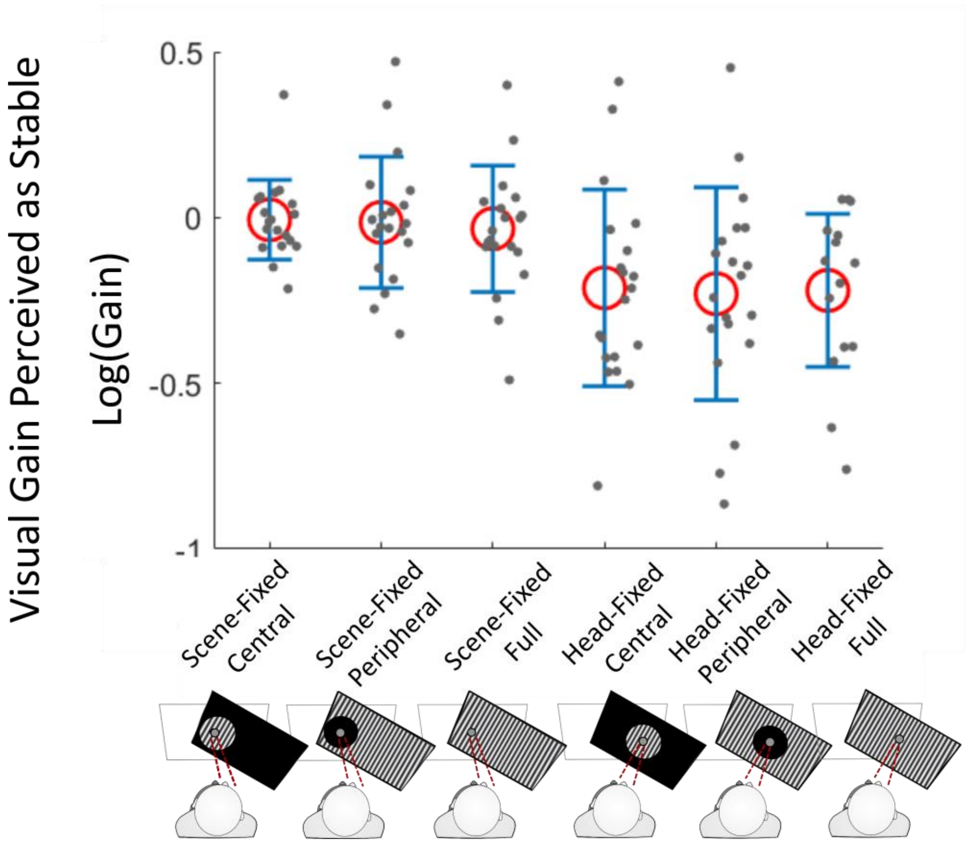
Scene-Fixed Condition

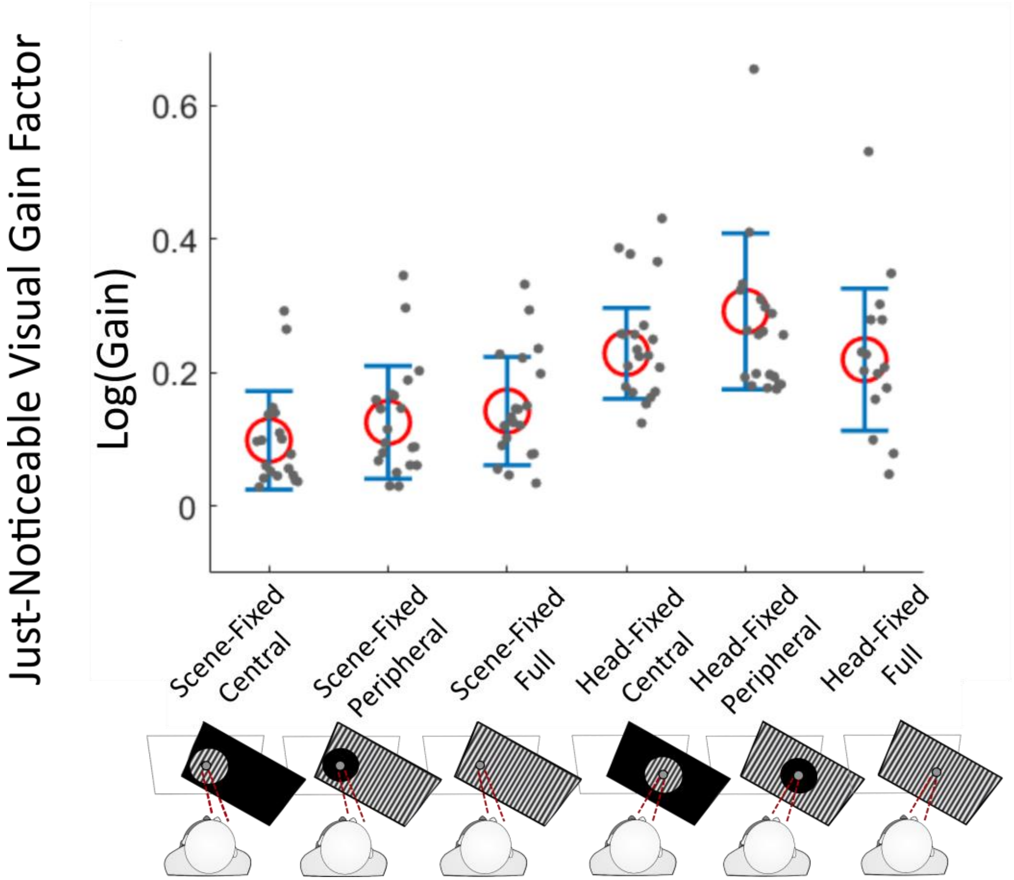


Head-Fixed Condition



PSEs and JNDs





Sensitivity depends on retinal stimulus location; these effects are mediated by fixation.

Outline

- Signal detection model of stationarity perception
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Stationarity perception and sickness

- Individual differences in:
  - Precision and accuracy of stationarity judgments
  - Susceptibility to sickness

- Are these related?

Measuring sickness

- Simulator sickness questionnaire
  - Nausea
  - Oculomotor discomfort
  - Disorientation
  - Total score

- Discomfort score
  - Average
  - Ending

No______________ Date____________________

SIMULATOR SICKNESS QUESTIONNAIRE

Kennedy, Lane, Berbaum, & Lilienthal (1993)***

Instructions : Circle how much each symptom below is affecting you right now.

1. General discomfort	None	Slight	Moderate	Severe
2. Fatigue	None	Slight	Moderate	Severe
3. Headache	None	Slight	Moderate	Severe
4. Eye strain	None	Slight	Moderate	Severe
5. Difficulty focusing	None	Slight	Moderate	Severe
6. Salivation increasing	None	Slight	Moderate	Severe
7. Sweating	None	Slight	Moderate	Severe
8. Nausea	None	Slight	Moderate	Severe
9. Difficulty concentrating	None	Slight	Moderate	Severe
10. « Fullness of the Head »	None	Slight	Moderate	Severe
11. Blurred vision	None	Slight	Moderate	Severe
12. Dizziness with eyes open	None	Slight	Moderate	Severe
13. Dizziness with eyes closed	None	Slight	Moderate	Severe
14. *Vertigo	None	Slight	Moderate	Severe
15. **Stomach awareness	None	Slight	Moderate	Severe
16. Burping	None	Slight	Moderate	Severe

Stationarity perception and sickness

- Is accuracy (PSE) correlated with sickness?

- Is precision (JND) correlated with sickness?

- Linear mixed effects modeling approach
  - R library lme4

$$SSQScore \sim PSE + JND + Fixation * RSL + Fixation * Frequency + (1|Subject)$$

Worse Accuracy -> Increased Sickness

- Simulator sickness questionnaire
  - ✓ Nausea
  - Oculomotor discomfort
  - Disorientation
  - Total score

- Discomfort score
  - Average
  - Ending

Sickness predicted by PSE	Coefficient of Fixed Effect	P value
Nausea	-12.13	p = 0.014
Oculomotor	-8.05	p = 0.289
Disorientation	-8.15	p = 0.311
Total Score	-10.39	p = 0.138
Average Discomfort	-0.100	p = 0.757
End Discomfort	-0.615	p = 0.167

Worse Precision -> Increased Sickness

- Simulator sickness questionnaire
  - Nausea
  - ✓ Oculomotor discomfort
  - ✓ Disorientation
  - ✓ Total score

- Discomfort score
  - Average
  - Ending

Sickness predicted by JND	Coefficient of Fixed Effect	P value
Nausea	12.54	$p = 0.289$
Oculomotor	36.17	$p = 0.045$
Disorientation	68.42	$p < 0.001$
Total Score	41.08	$p = 0.013$
Average Discomfort	0.361	$p = 0.631$
End Discomfort	-1.67	$p = 0.113$

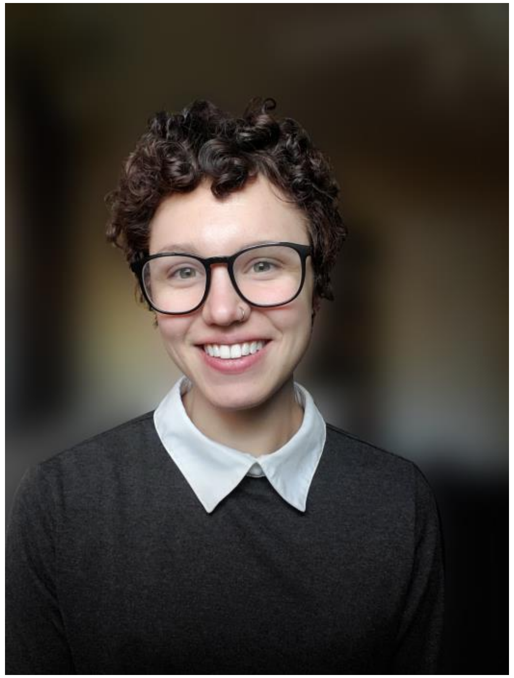
Conclusions and future directions

- Stationarity paradigm allows identifying self-motion factors
  - Integration of visual signals driving visual self-motion
  - Interactions with motor signals

- Future directions
  - Other motion axes/direction
  - Investigate dynamics; how information is integrated over time? (Garzroz & MacNeilage 2019)
  - May be modeled in a causal inference framework
  - Physiological correlates

Acknowledgments

- Savannah Halow



Self-motion Lab

National Science Foundation
WHERE DISCOVERIES BEGIN

NIH
National Institutes of Health

- Research was supported by NIGMS of NIH under grant number P20 GM103650 and NSF CHS under grant 1911041