Drift Gain Study

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November 2, 2016

Study Objectives

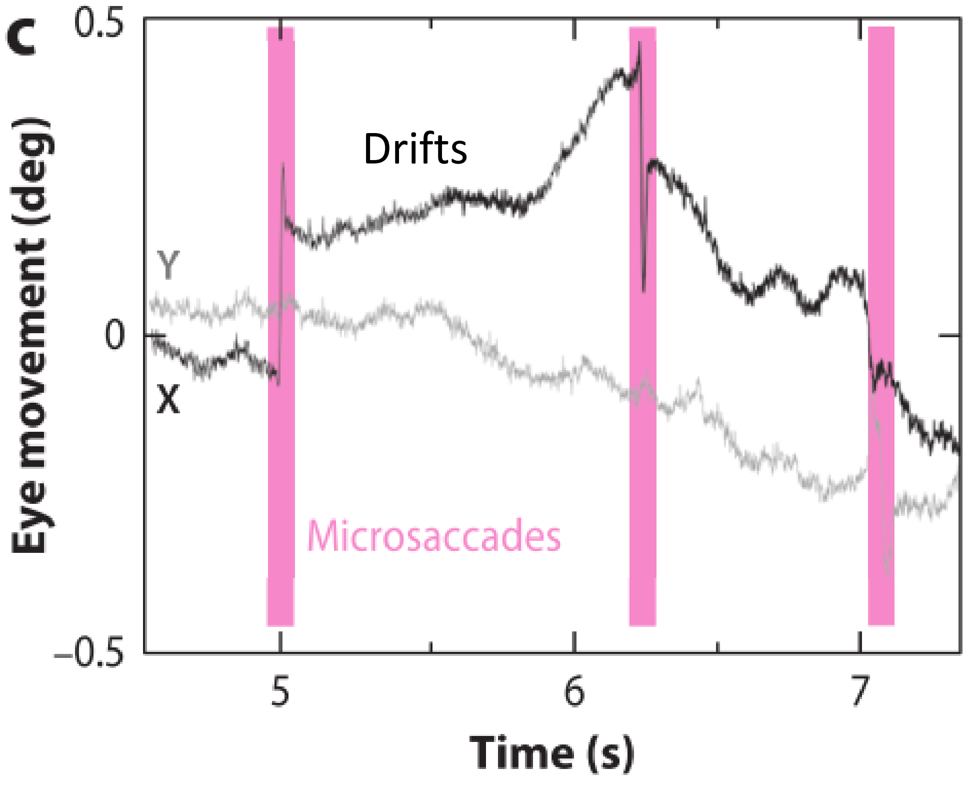
- Drift creates temporal modulations in the visual input to the retina
- Do we control our drift to maintain certain temporal modulations?
- Can altering these temporal modulations predictably improve or impair vision?
  - By changing drift behavior
  - By manipulating the stimulus

Overview

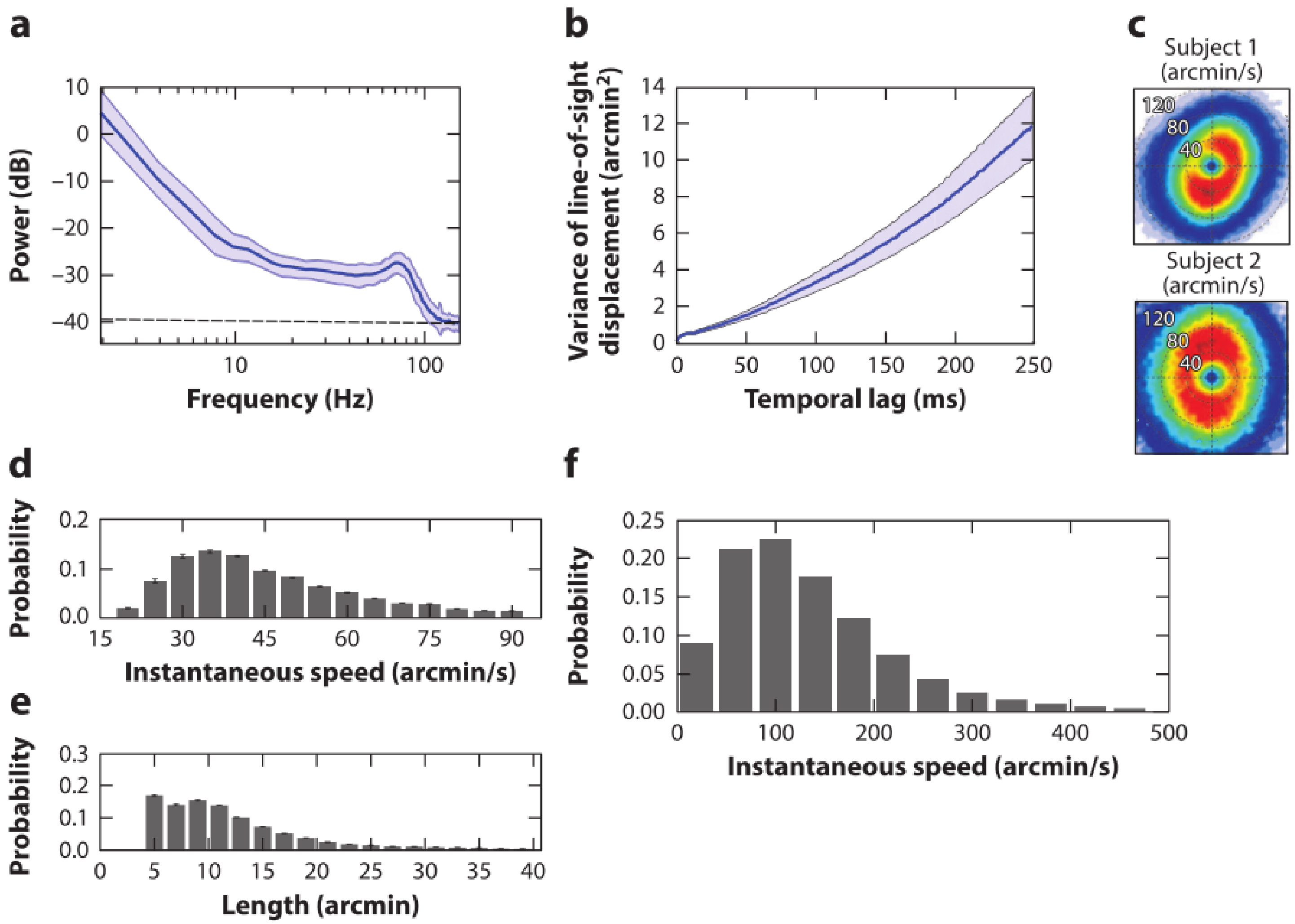
- What is ocular drift and how is it simulated?
- Theoretical construct of contrast sensitivity predictions
- Review of Drift Gain Experiments: Free View and Grating
- Comparison of prediction with experimental results
- Next Steps

What is ocular drift?

- Slow, erratic motion that occurs between saccadic gaze shifts



Drift (and tremor) characteristics during fixation



Figures from Rucci & Poletti, 2015; Annual Review of Vision Science

Is drift useful? Do we control it?

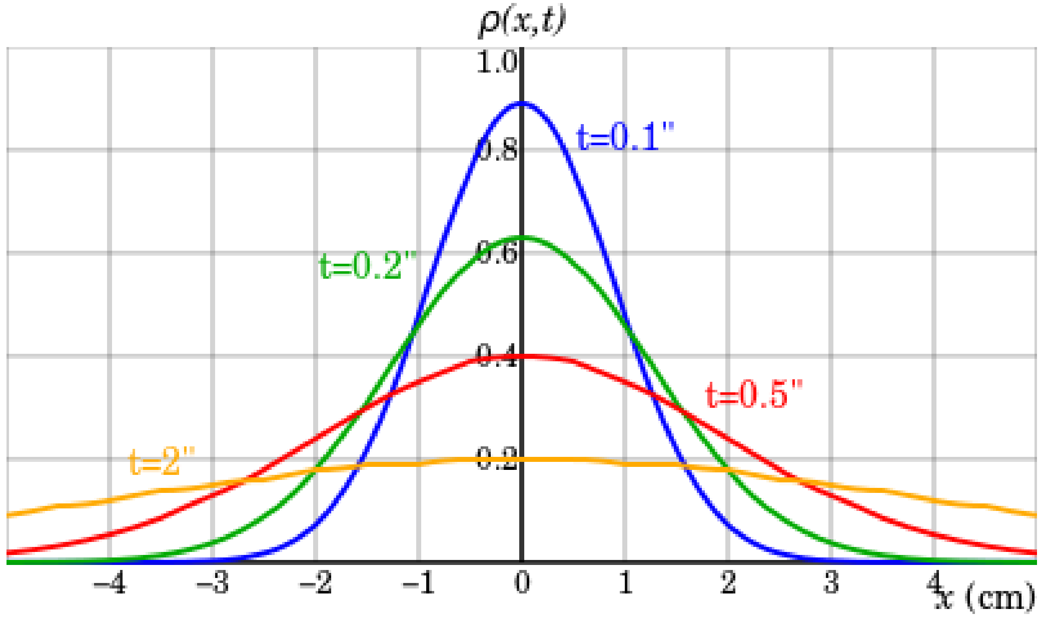
- Enhance fine spatial detail (Rucci et al., 2007)
- Prevent fading

- evidence of **slow control**
  - Drifts are error-correcting, zero-velocity smooth pursuit (Nachmias, 1961; Epelboim & Kowler, 1992)
  - “fixate” vs “hold eyes still” (Steinman et al., 1973)
- Drift shows characteristics similar to a random walk (Engbert & Kliegl, 2004)

Random Walks: A diffusion model

- Brownian Motion
  - One dimensional example
  - At every time step, a particle moves left or right with equal probability
  - On average, the particle doesn't go anywhere (mean 0 displacement)
  - The variance of the displacement is described by *D*, the diffusion coefficient

$$\langle x^2 \rangle = 2Dt$$

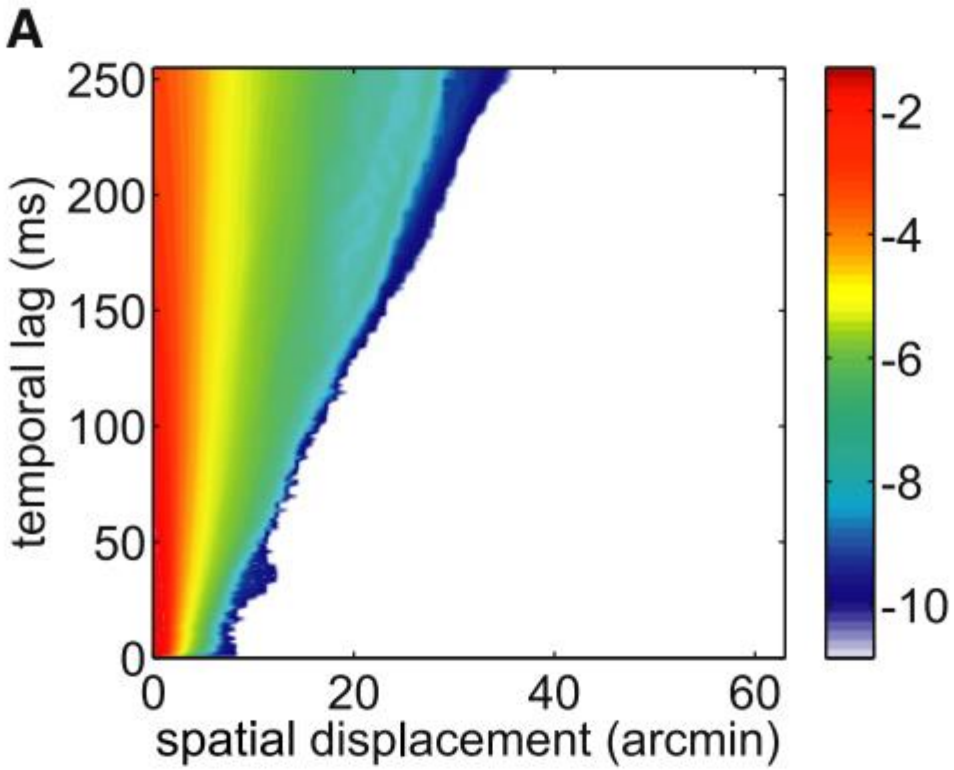


$$p(x,t) = \frac{1}{4\pi Dt} \exp\left(-\frac{x^2}{4Dt}\right)$$

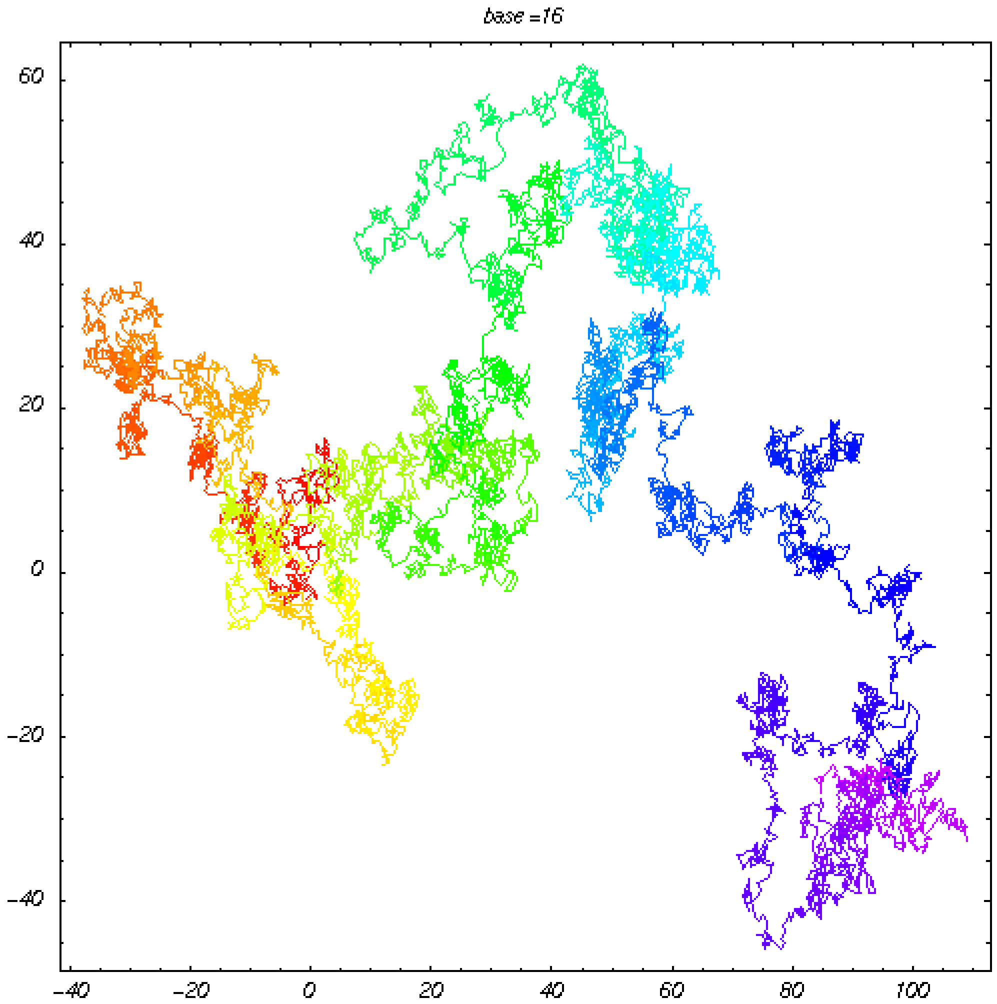
Diffusion Model of Ocular Drift

$$q(x, y, t) = \frac{1}{4\pi D_R t} \exp\left(-\frac{x^2 + y^2}{4 D_R t}\right)$$

D_R = retinal diffusion coefficient

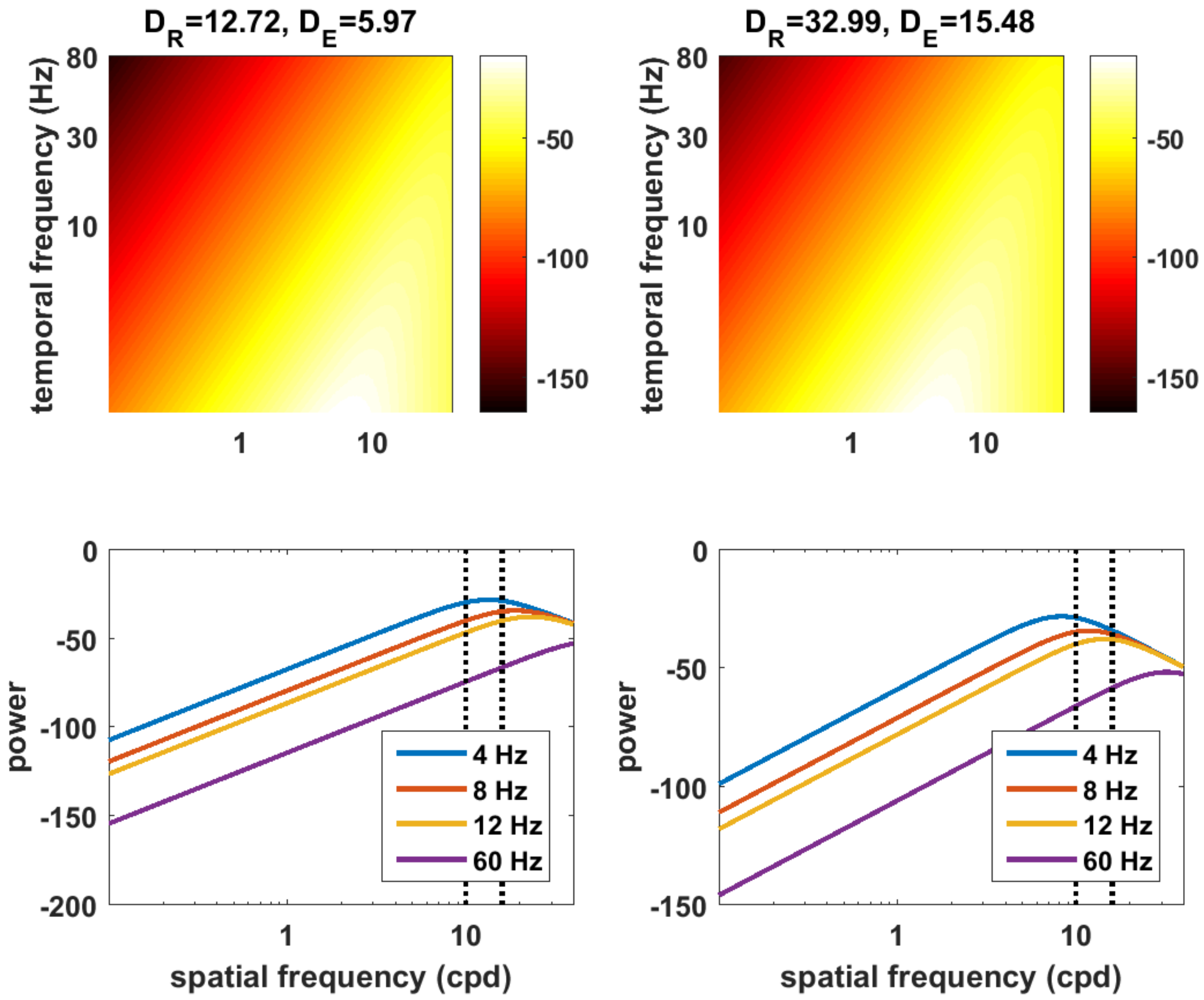


Kuang et al., 2012



http://functions.wolfram.com/Constants/Pi/visualizations/2/ShowAll.html

Spatiotemporal frequency content of retinal motion during modeled drift

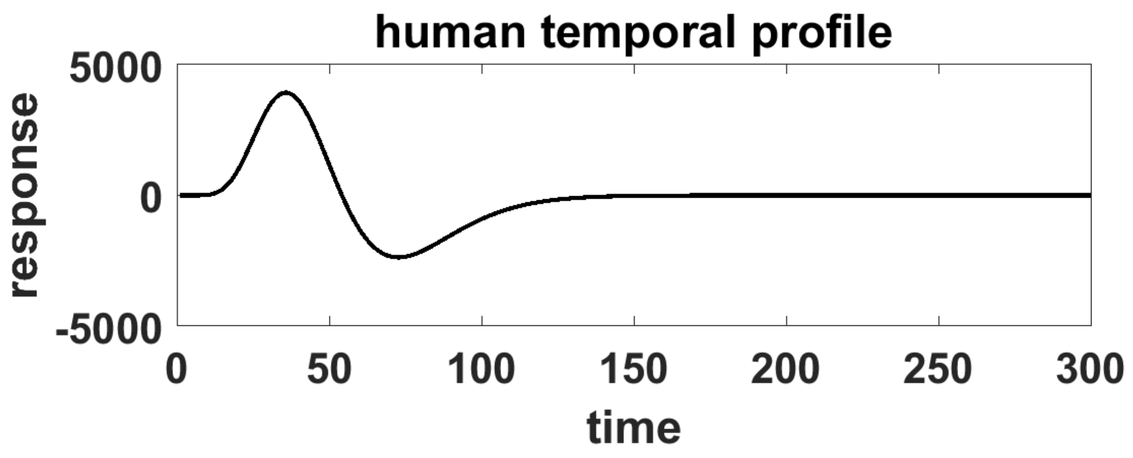


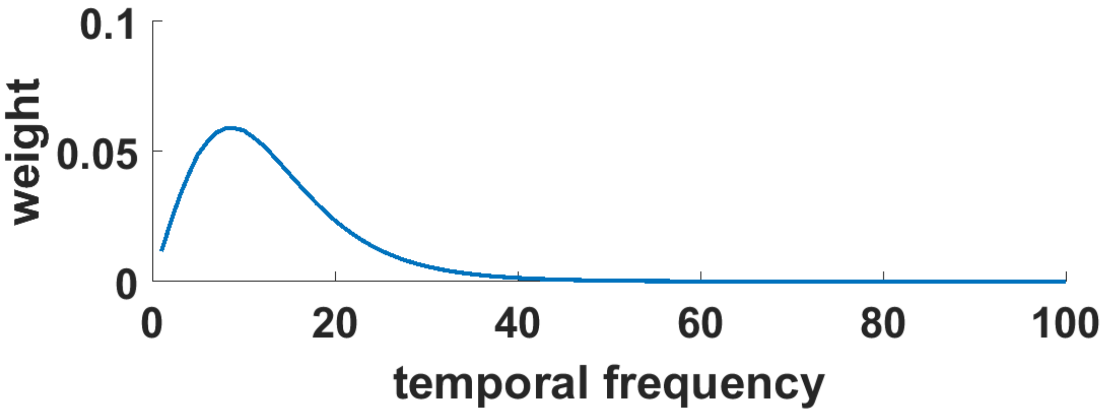
$$Q(\xi_x, \xi_y, f) = \frac{2D_R(\xi_x^2 + \xi_y^2)}{4\pi^2 D_R^2(\xi_x^2 + \xi_y^2)^2 + f^2}$$

ξ_x, ξ_y= spatial frequencies
f = temporal frequency

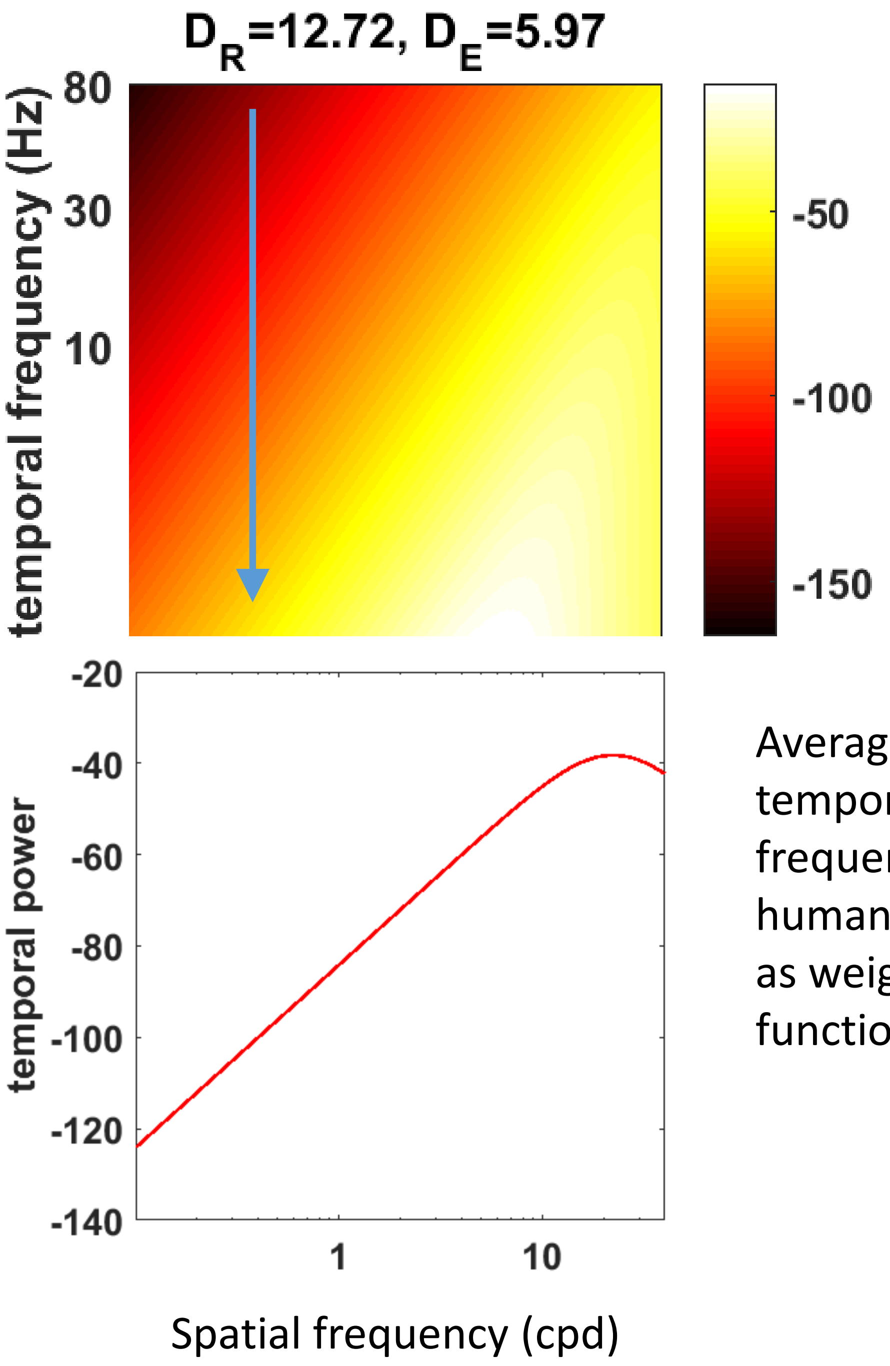
Power increases proportionally to the spatial frequency squared (amplification) up to some critical spatial frequency

Human temporal sensitivity



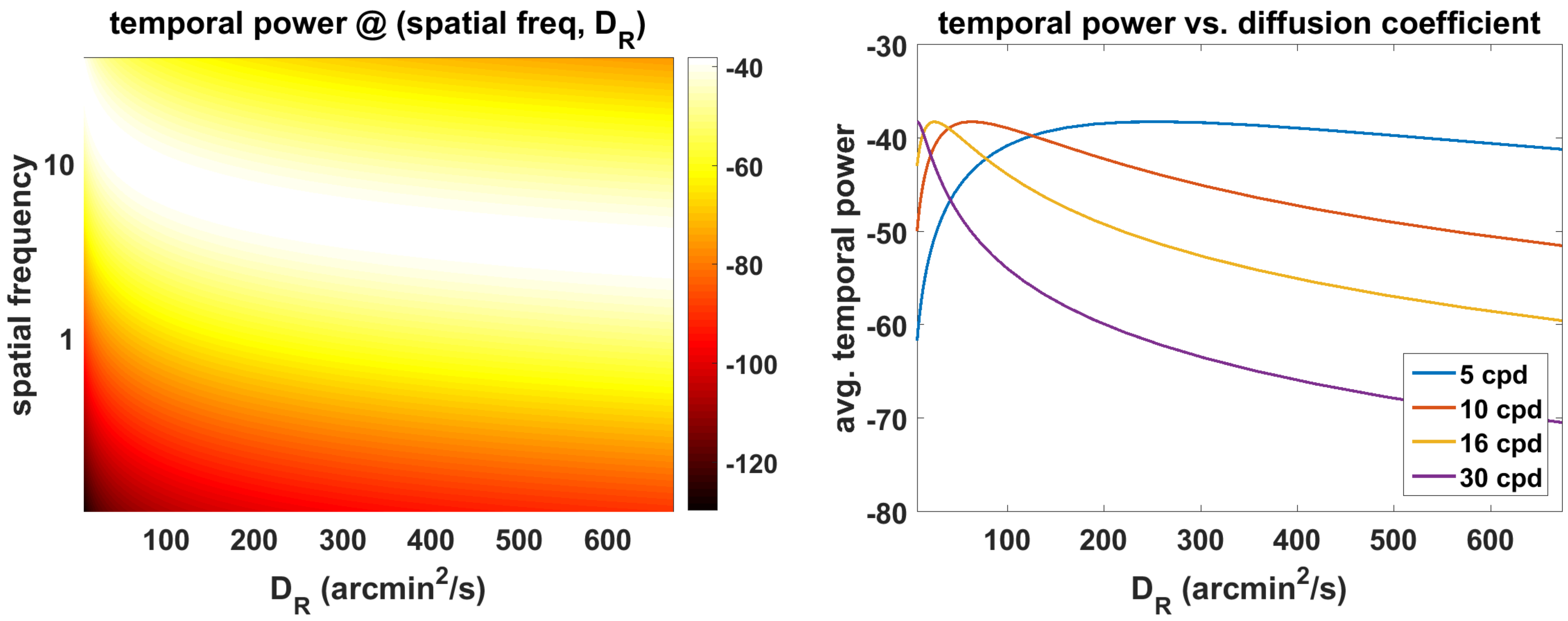


Linear Filter model of human temporal sensitivity as described by Watson (1986). Parameters chosen reflect transient response (Roufs & Blommaert, 1981).



Average over temporal frequencies using human sensitivity as weighting function

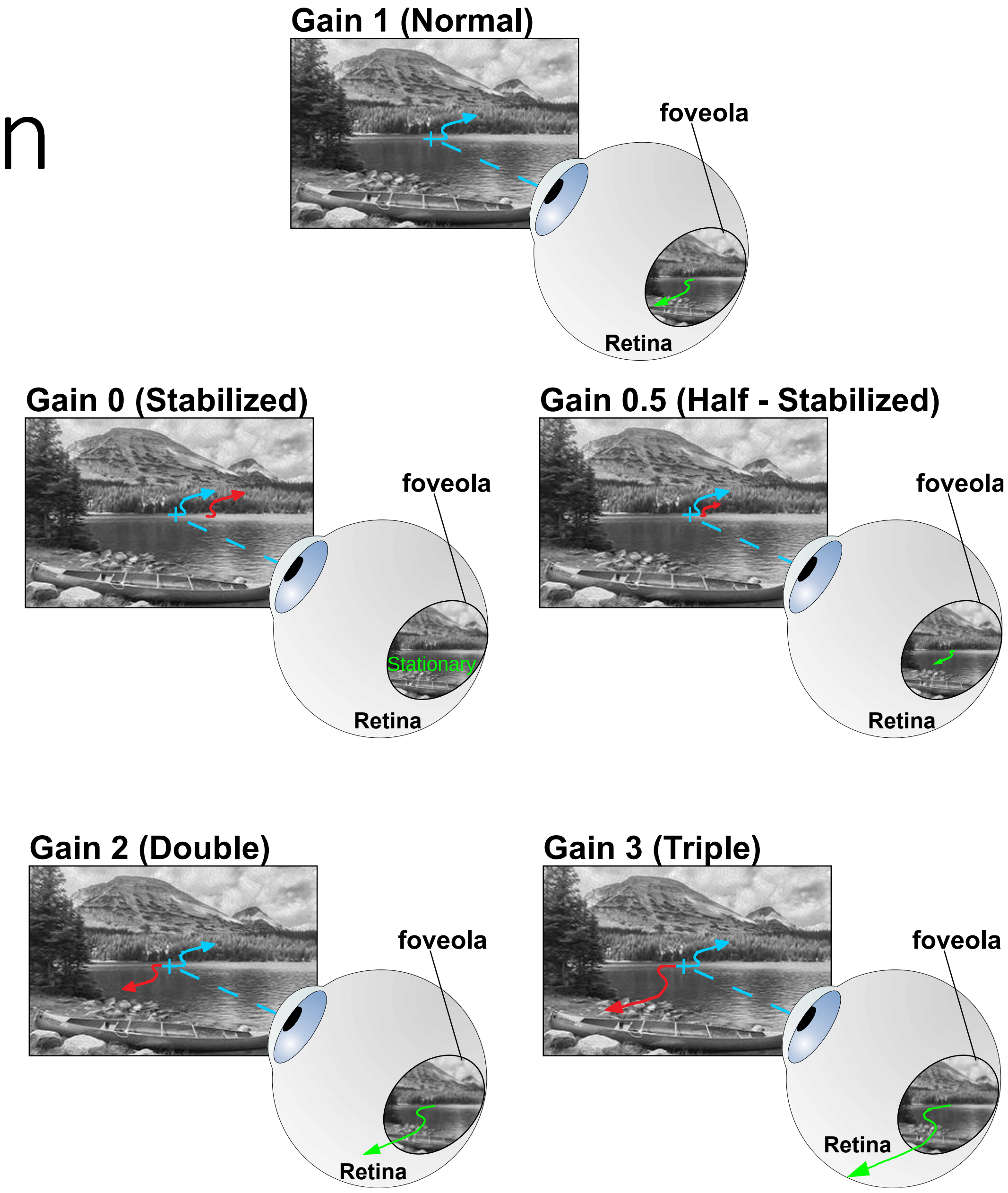
What if the retinal diffusion changes?



Prediction: There is an optimal drift behavior (D_R) that maximizes sensitivity at each spatial frequency.

Modulating retinal motion

- Gaze contingent display is used to amplify or reduce retinal motion by some gain
- **Free View** experiment: Do subjects adjust drift behavior to compensate for altered retinal image motion?
- **Grating** experiment: Can sensitivity be improved by manipulating retinal image motion?



From Norick's DriftGain report

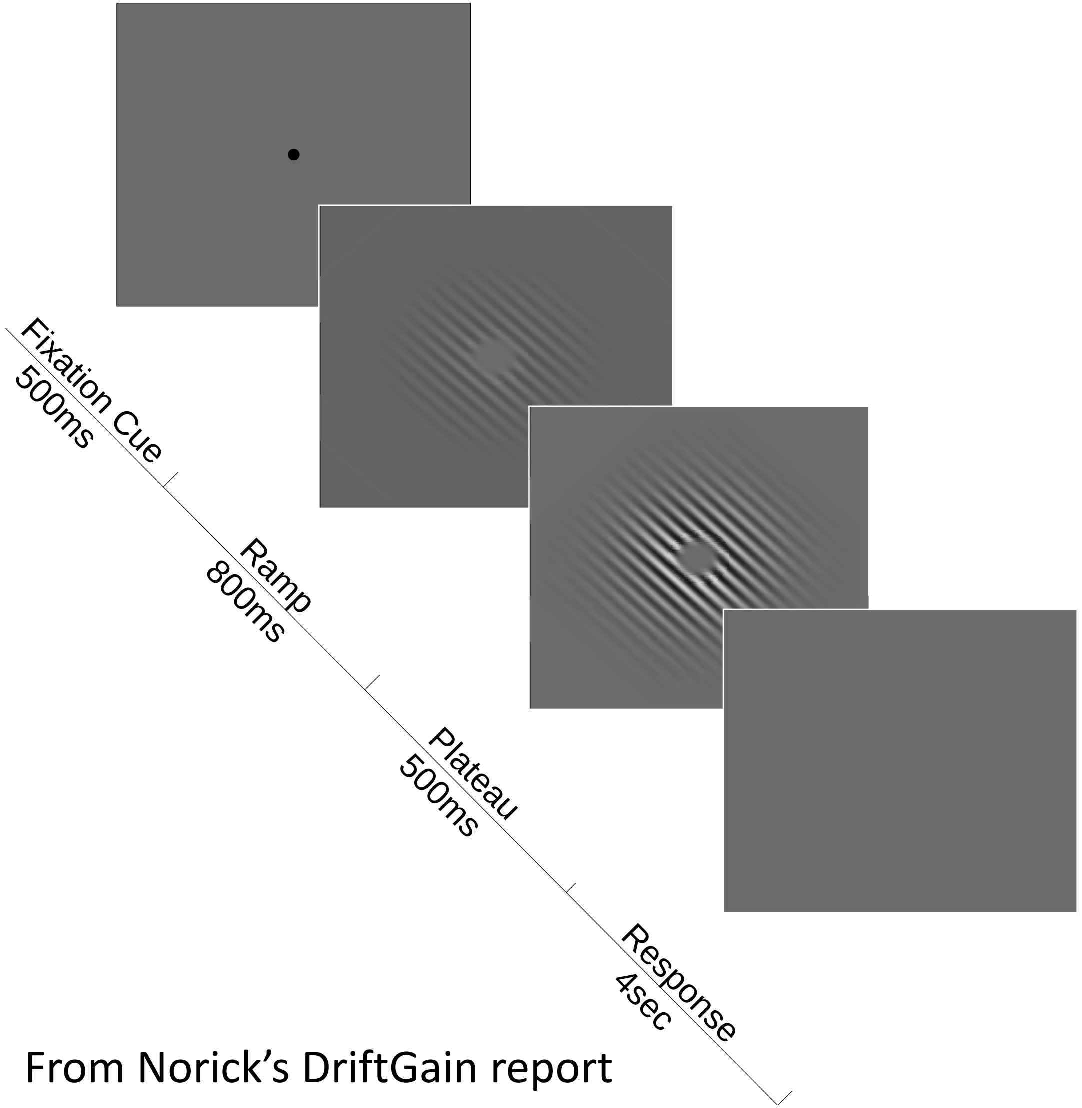
Free View: Conclusions

- Drift changes to compensate for retinal motion
  - decreased curvature when not enough motion; increased when too much
  - Indications of larger span, higher speeds when not enough motion
- Drift is not entirely a random walk
  - Characteristics change over time
  - Displacement-squared does not increase linearly with time
  - Fractional Brownian motion could serve as a better model (Engbert & Kliegl, 2004)

Grating: Inconclusive

- Effects in free view conditions were not seen in grating experiment

Grating Experiment

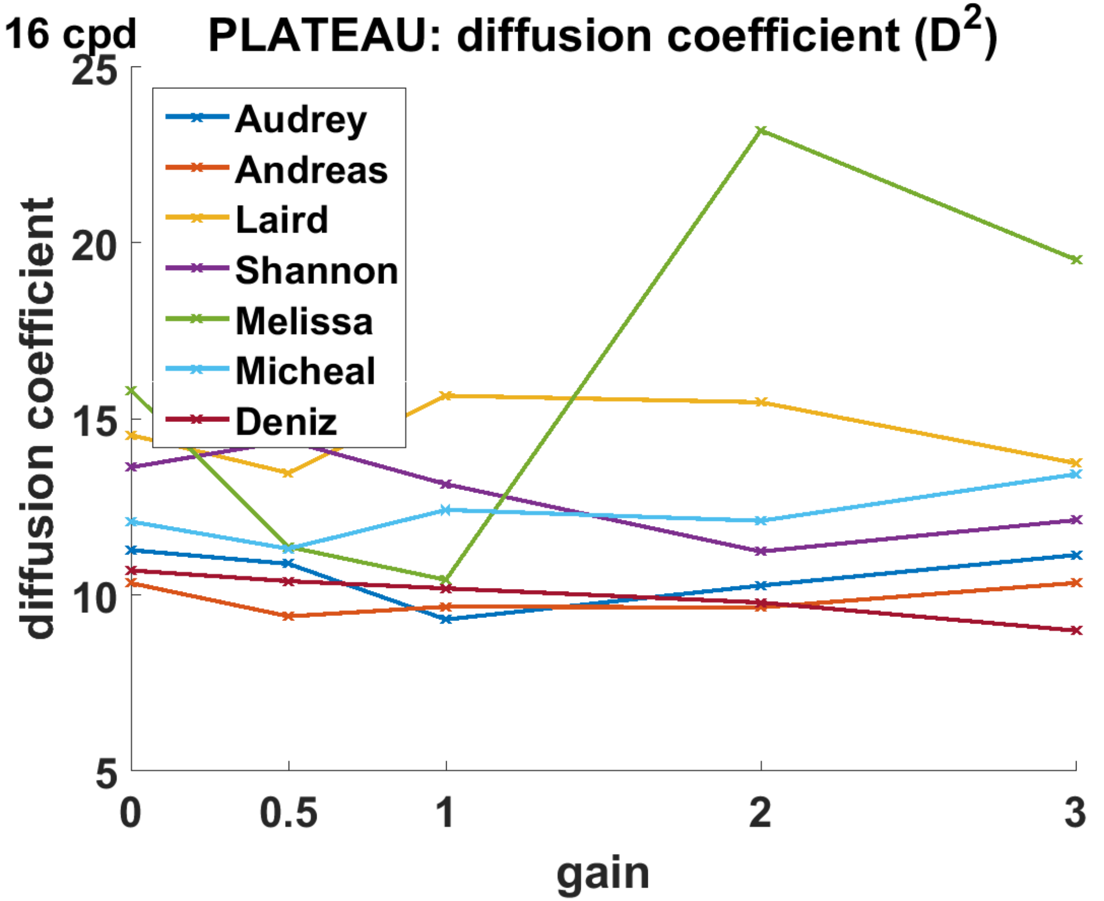


From Norick's DriftGain report

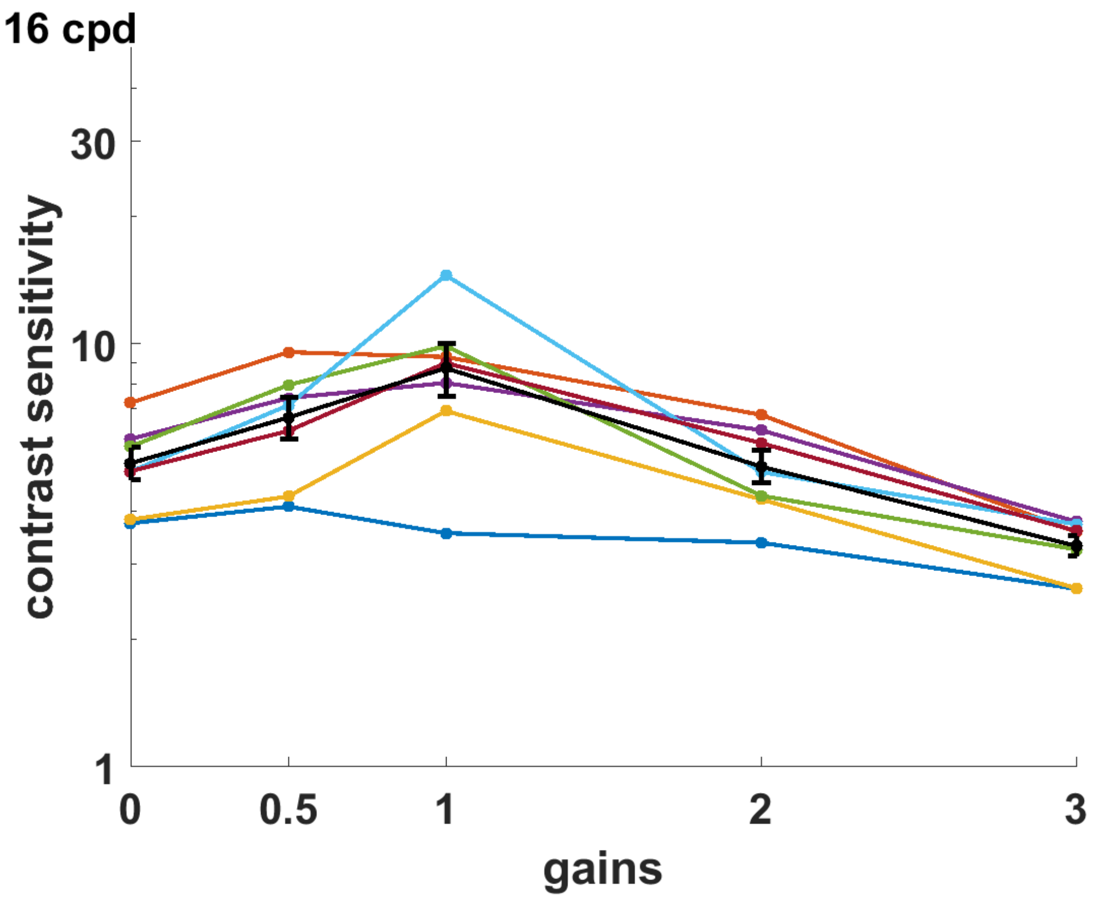
- 2AFC task: What is the orientation of the grating?
- 1 deg scotoma prevented vision of grating in high acuity foveola
- Contrast of the gratings updated following the PEST algorithm in order to determine the 75% contrast threshold
- First data set:
  - 16 cpd gratings
  - Gains = [0, .5, 1, 2, 3]
  - 7 Subjects
- Second data set:
  - 16 and 10 cpd gratings
  - Gains = [.75, 1, 1.2]
  - 3 subjects

Data Set 1

$$CS = \frac{I_{\max} + I_{\min}}{I_{\max} - I_{\min}}$$



For most subjects, diffusion coefficient *D* was invariant to gain

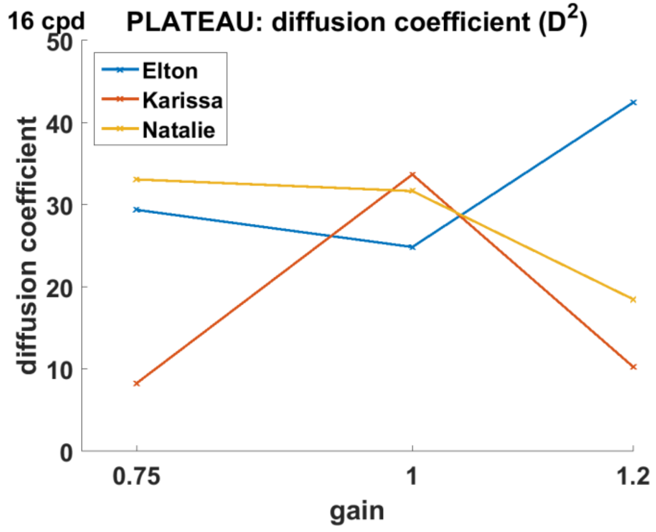


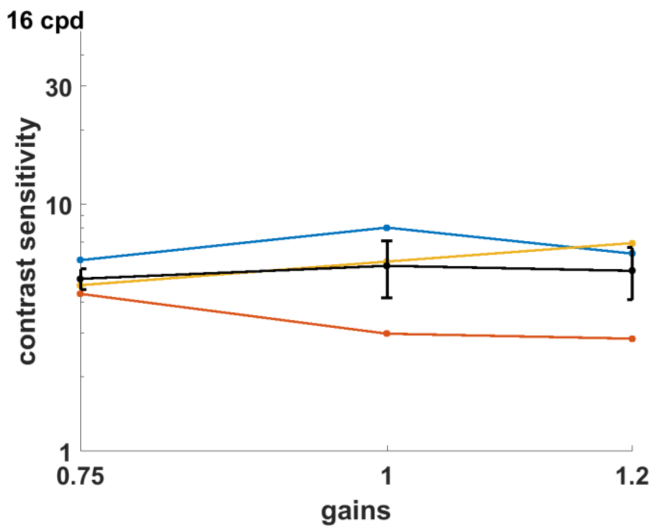
For most subjects, contrast sensitivity was highest under normal viewing conditions (gain = 1)

Data Set 2: not as clear

$$CS = \frac{I_{\max} + I_{\min}}{I_{\max} - I_{\min}}$$

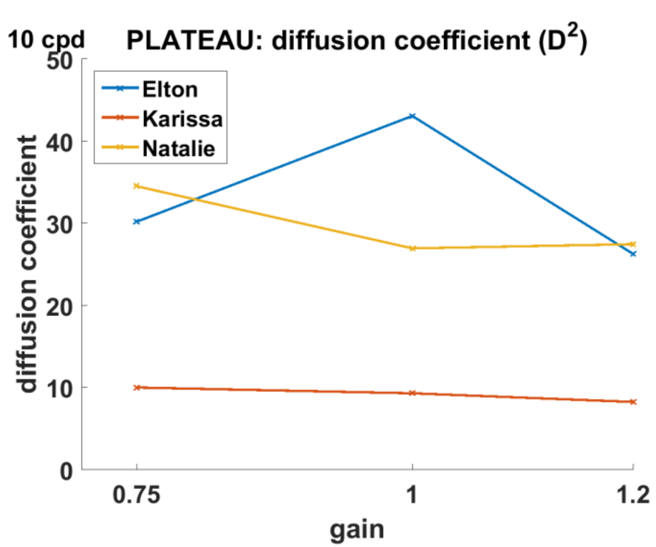
16 cpd

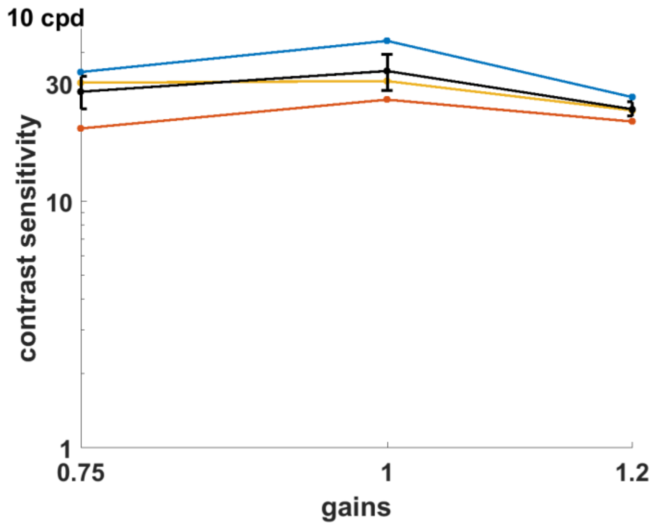




- Subjects' *D* varied at different gains; more diffuse
- No apparent change in performance across different gains

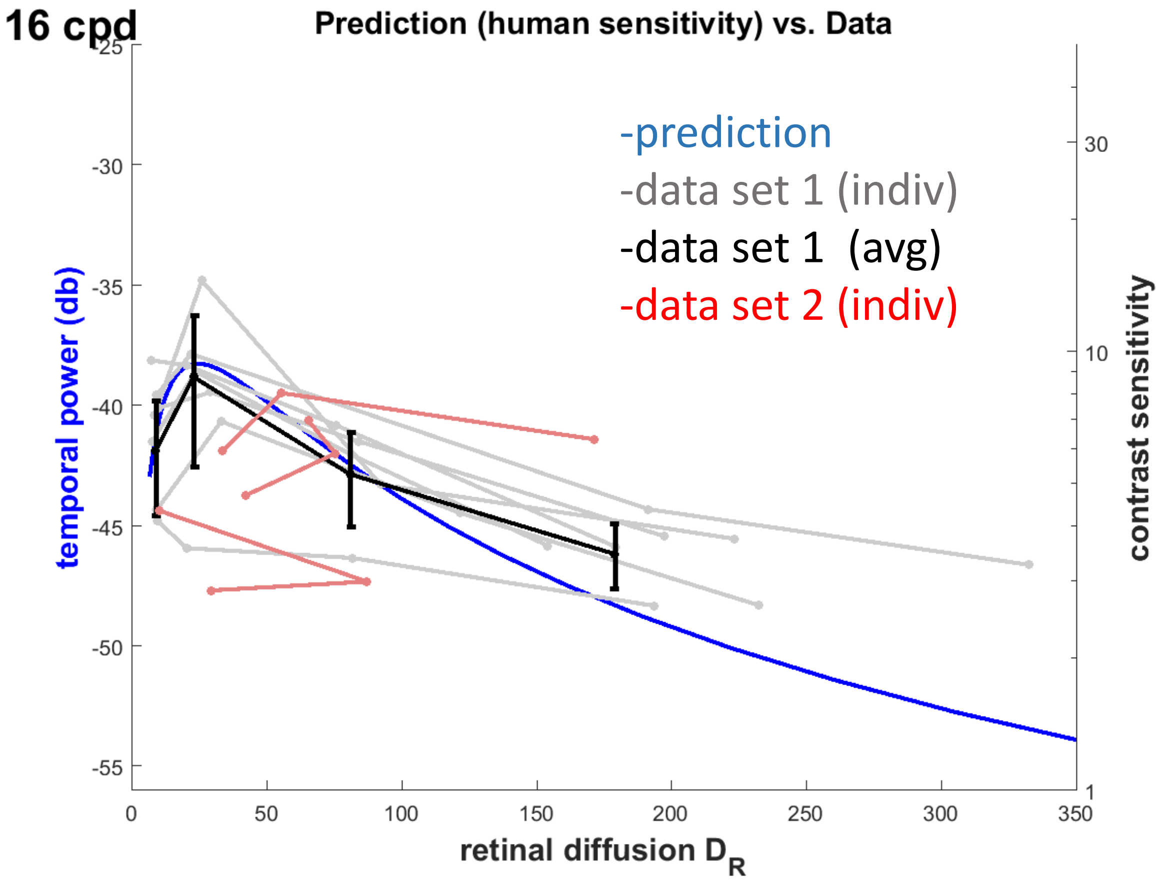
10 cpd





- Better contrast sensitivity at 10 cpd than at 16 cpd (expected)

Did we predict this data? (16 cpd)

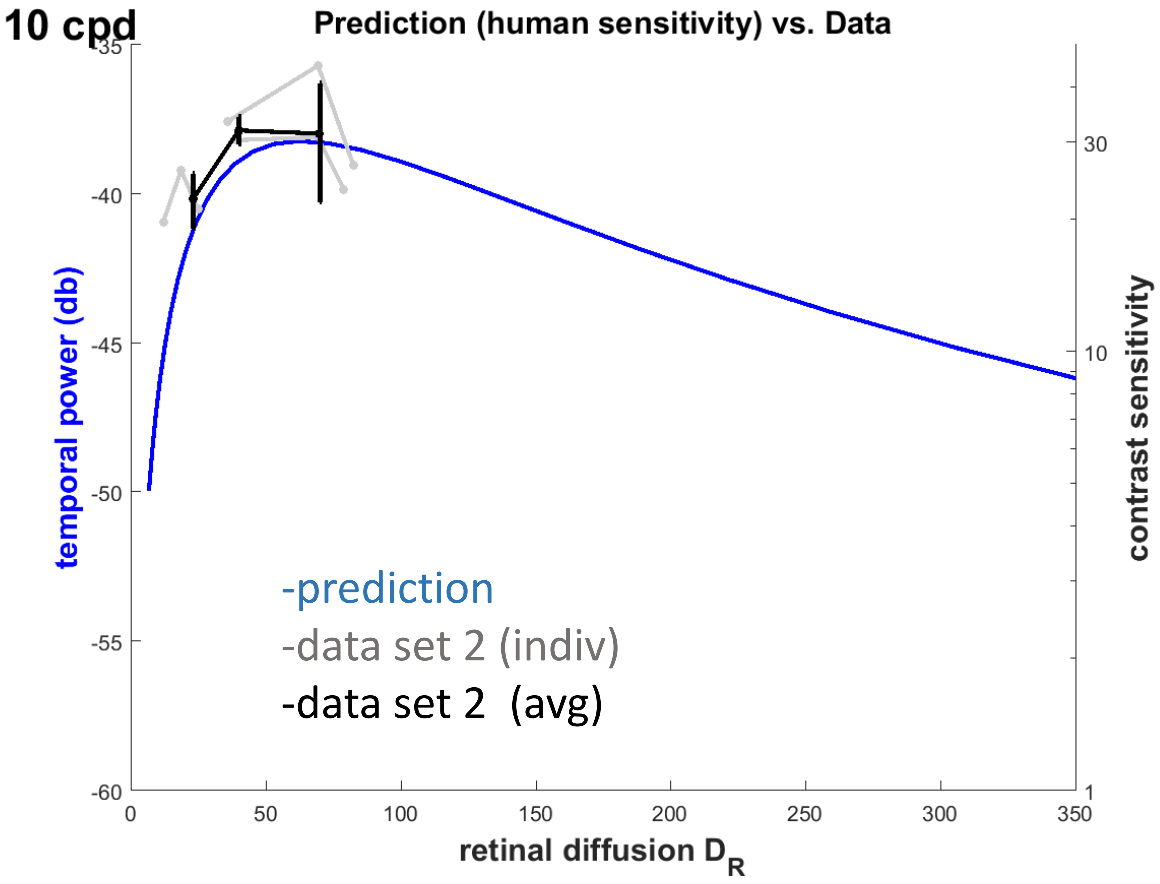


- Drift in normal conditions already matched optimal drift behavior – increasing or decreasing gain impaired performance
- Data set 2 is less consistent with the prediction – why?
  - Drastically changing D_R between gain conditions

Prediction and contrast sensitivity scaled arbitrarily to match as closely as possible.

Did we predict this data? (10 cpd)

- Not enough data?
- General trend shows that the subject with smallest D_R has the worst overall sensitivity



Prediction and contrast sensitivity scaled arbitrarily to match as closely as possible.

Next Steps

- 10 and 16 cpd have similar predictions, try a grating which could have drastically different results? (example 5cpd)
- Problem: contrast sensitivity is very high near 5cpd, do we have the contrast resolution for this?