

CONSTRAINTS ON DECODING OF VISUAL MOTION PARAMETERS FOR SMOOTH PURSUIT FROM CORTICAL POPULATION ACTIVITY

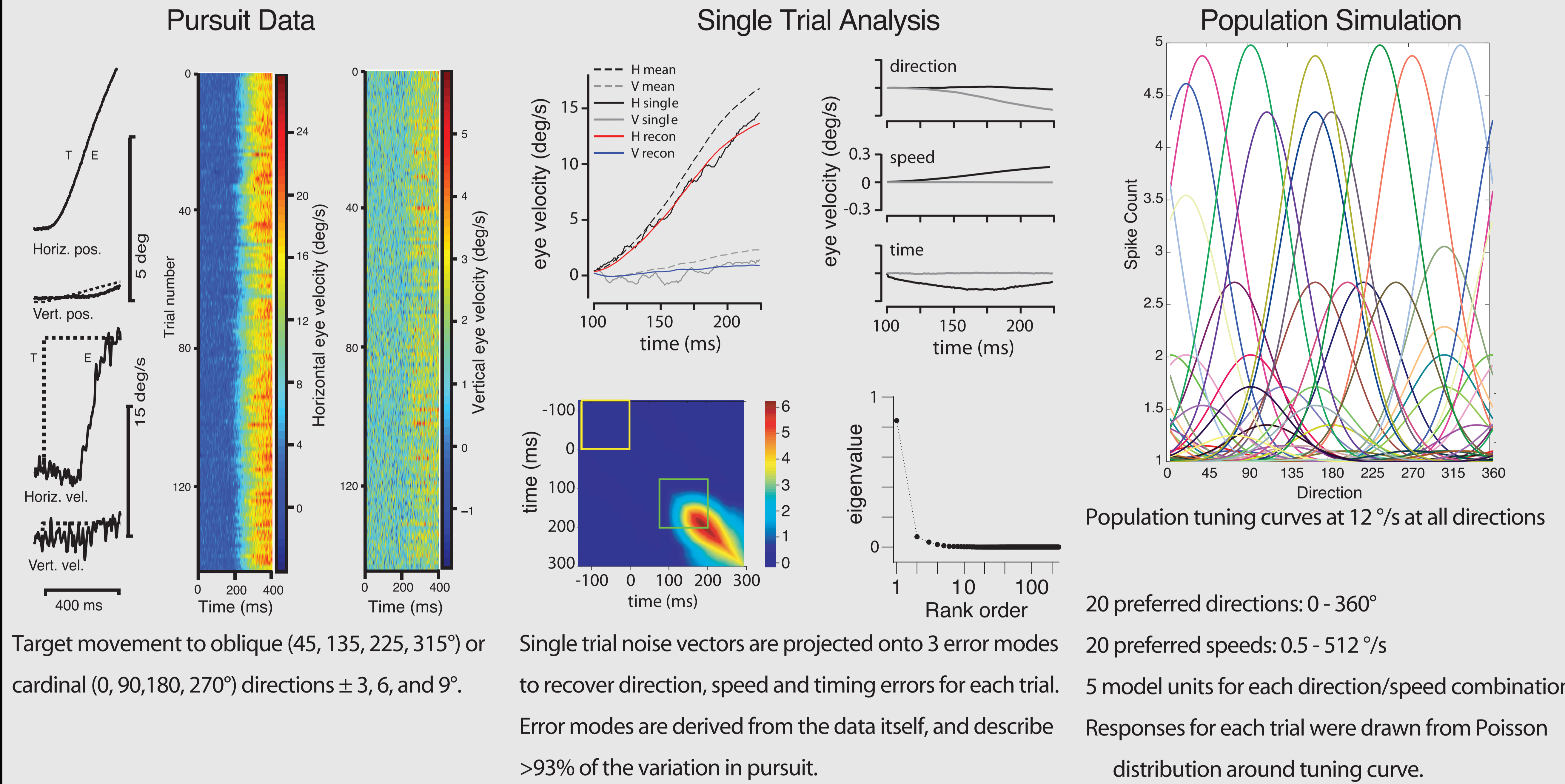
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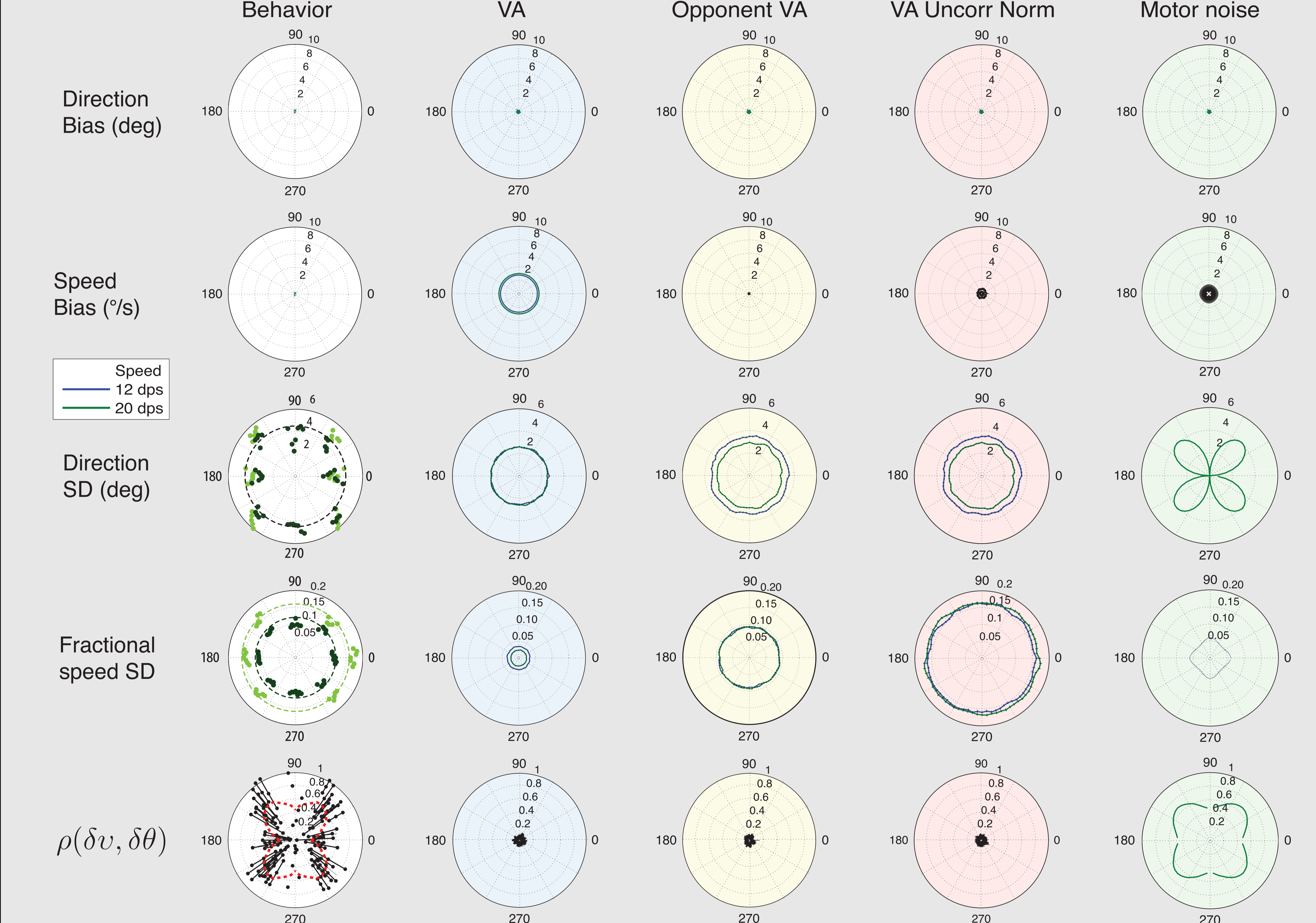
Introduction

Analysis of sensory-motor behaviors can be very useful for increasing our understanding of the computations being performed by circuits within the brain. Visual smooth pursuit, a task in which the eyes move to stabilize the retinal image of a target, provides an ideal testbed for this type of analysis, as minimal motor noise is added to initial sensory estimates of an object's retinal image motion. Neurons in the middle temporal area (MT) of the primate extrastriate visual cortex have been shown to be selectively responsive to retinal image motion, and exhibit direction and speed-preferential spike tuning. Here, we analyze the structure of smooth pursuit eye movements, and compare the results to the structure of estimates of decoding methods based on responses from model MT units. These methods differ in how the variance in neural responses is transformed as visual information propagates through the visual system, and we can use this property to determine which methods may be describing computations that the visual system is actually performing. We find that the correlation between direction and speed errors at the end of smooth pursuit is significantly higher at oblique directions than at cardinal directions. Existing population decoding methods, including maximum likelihood and multiple forms of vector averaging, fail to capture this phenomenon. Although a motor noise model that adds signal-dependent variance to horizontal and vertical speed components recreates the oblique pattern of correlations between direction and speed noise, it also adds directional structure to direction and speed variance.

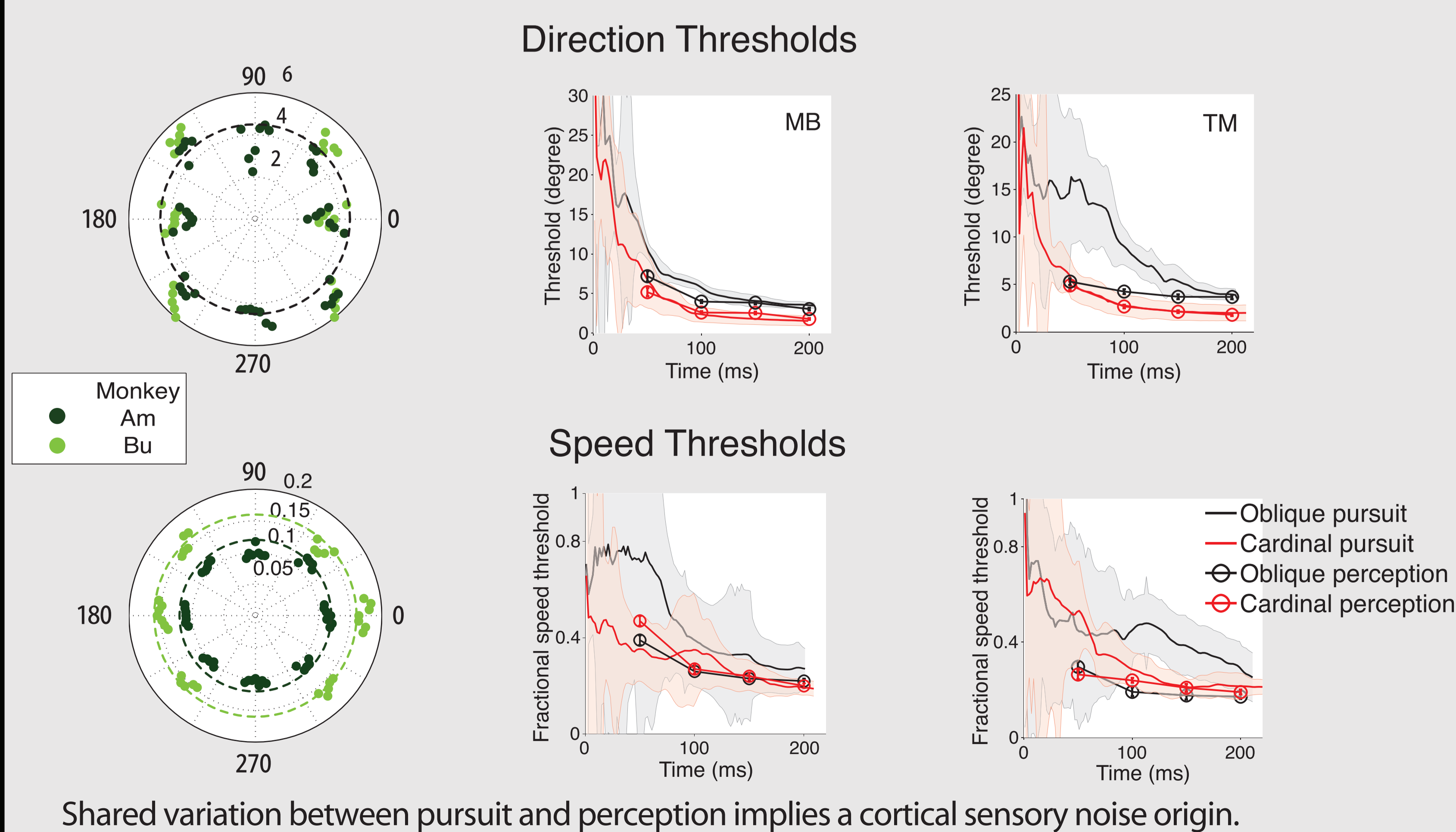
Experiments



Simulation Results



Behavioral Results



Decoding Methods

Vector Averaging (VA)

$$\hat{\theta} = \tan^{-1} \left(\frac{\text{Im}(\sum_i R_i e^{i\theta_p})}{\text{Re}(\sum_i R_i e^{i\theta_p})} \right) \quad \hat{s} = \frac{\sum_i R_i \log_2 s_p}{\sum_i R_i}$$

Opponent Vector Averaging (Opponent VA)

$$R_h = \sum_i \cos(\theta_p) R_i \quad R_v = \sum_i \sin(\theta_p) R_i$$

$$\hat{H} = \frac{\sum_i \log_2(s_p) \cos(\theta_p) R_i}{\epsilon + \sqrt{R_h^2 + R_v^2}} \quad \hat{V} = \frac{\sum_i \log_2(s_p) \sin(\theta_p) R_i}{\epsilon + \sqrt{R_h^2 + R_v^2}}$$

$$\hat{\theta} = \tan^{-1} \left(\frac{\hat{V}}{\hat{H}} \right) \quad \hat{s} = 2\sqrt{\hat{H}^2 + \hat{V}^2}$$

Opponent Vector Averaging normalized by uncorrelated population (VA Uncorr Norm)

$$\hat{H} = \frac{\sum_i \log_2(s_p) \cos(\theta_p) R_i}{k \sum_i R_i} \quad \hat{V} = \frac{\sum_i \log_2(s_p) \sin(\theta_p) R_i}{k \sum_i R_i}$$

$$\hat{\theta} = \tan^{-1} \left(\frac{\hat{V}}{\hat{H}} \right) \quad \hat{s} = 2\sqrt{\hat{H}^2 + \hat{V}^2}$$

Parameters were fit to minimize the direction and speed bias of estimates.

Discussion

Significant direction-speed error correlations at oblique angles
 No decoding model we have tested captures correlations
 Common decoding models fail to predict at least one other behavioral parameter
 Next steps:
 More realistic MT population: tuning curve heterogeneity and between-neuron correlations
 Develop new decoding models

References

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 Osborne LC, Hohls S, Blake W, Lisberger SG. Time course of precision in smooth-pursuit eye movements of monkeys. *J Neurosci* 27:2987-2998, 2007.
 Rashbass C. The relationship between saccadic and smooth tracking eye movements. *J Physiol* 159:326-338, 1961.

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