Modeling the Trial-by-Trial Influence of Fixational Eye Movements on Visual Discrimination

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OVERVIEW

Our research goal is to understand the impact of fixational eye movements on perception. To this end, here we develop a computational model of the effect of fixational eye movements on trial-by-trial neural signals and visual discriminations.

BACKGROUND

Fixational Eye Movements (FEMs)

Characteristics

Microsaccade
Saccades with amplitudes smaller than 0.5 deg. Typical rate 1-2 times every second.

Ocular drift
Slow eye movement within the foveal range. Typically < 1 deg/s

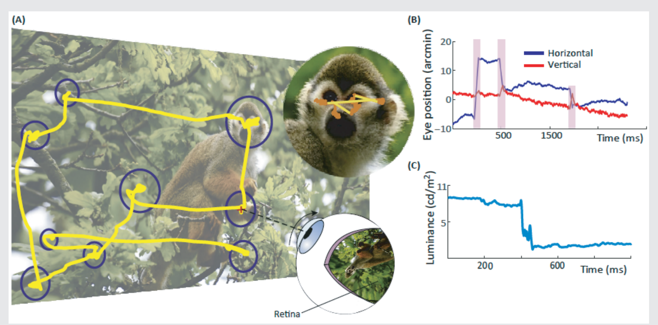


Figure credit: Rucci, Ahissar, and Burr (2018) Trends Cogn Sci.

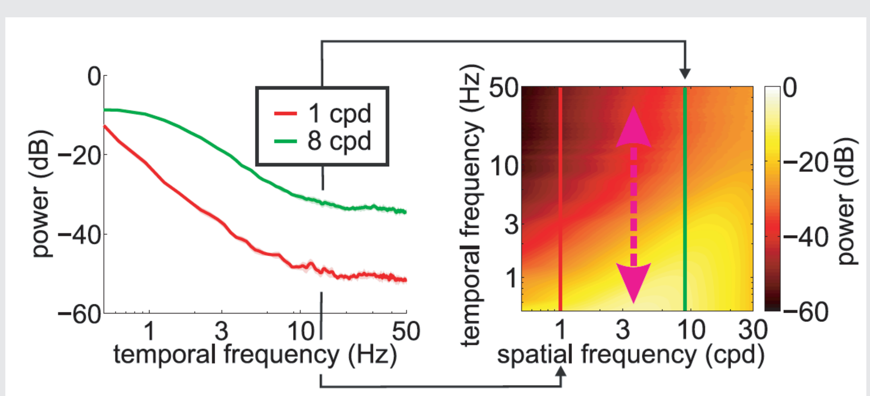
Functions

Microsaccades
- Spatial selection

Ocular drift
- Feature extraction
- Remove statistical redundancy from natural scenes

MOTIVATION

Oculomotor Strategy for Temporal Coding Visual Space



Ocular drift modulates input signals in a way that depends on the spatial frequency of the stimulus. The same amount of drift yelds larger temporal fluctuations at higher spatial frequencies. Higher spatial frequences lead to broader temporal distributions. *(Casile et al. 2019. Elife)*

Do FEMs Have Influence on Perception?

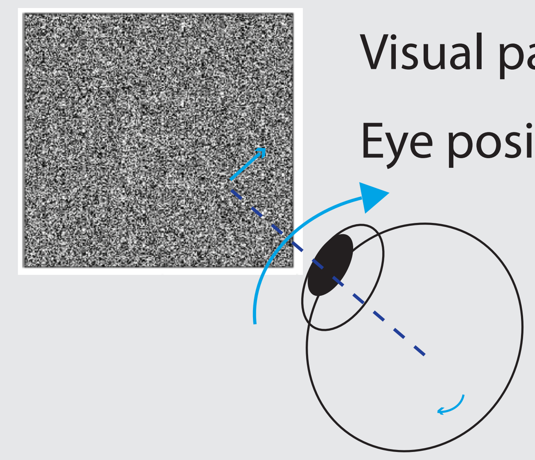
It is known that eliminating drift movements selectively impairs sensitivity at high spatial frequencies. To understand the influence of FEMs on a trial-by-trial basis and visual discrmination, a simulation model is needed. The model we built tests the extent to which different eye movement trajectories influence discrimination performance, helps to understand the roles of different classes of LGN neurons in making use of FEM dynamics, and formalizes a link between fixational eye movements, neural activity, and behavioral responses.

ACKNOWLEDGEMENTS

This project is supported by NIH EY07977, EY18363 and the Fred Plum Fellowship in Systems Neurology and Neuroscience.

MODEL

Visual Inputs



Visual pattern $I(x,y) = image(x,y) + noise(x,y)$

Eye positions $X(\tau)$ and $Y(\tau)$ (measured at Rucci lab)

Contrast ramp $R(\tau)$

Retinal stimulus

$$S(x,y,\tau) = I\left[x - X(\tau), y - Y(\tau)\right] * R(\tau)$$

Neural Responses at the LGN level

Firing rate of individual cell: linear model followed by rectification

$$l_{xy}(\tau) = \left[K(x,y,\tau) * S(x,y,\tau)\right]_+$$

$[\bullet]_+$ indicates rectification, where $[x]_+ = \max(0,x)$

Receptive field model: center and surround each with separable spatial (F) and temporal (G) components. *(Rucci et al. (2000) J. Neurosci.)*

$$K(x,y,\tau) = F_c(x,y)G_c(\tau) - F_s(x,y)G_s(\tau)$$

(c: center, s: surround)

Spatial profile (F_c and F_s): 2D circular Gaussian distribution

$$F(x,y) = Ke^{\frac{-(x^2+y^2)}{2\pi\sigma^2}}$$

K is the strength and σ is the radius

Temporal profile (G_c and G_s): a series of low-pass and high-pass stages

$$\tilde{G}(\omega) = Ae^{-i\omega D}\left(1 - \frac{H_s}{1+i\omega\tau_s}\right)\left(\frac{1}{1+i\omega\tau_L}\right)^{N_L}$$

Spatial and temporal parameters (K, A, σ, D, H_s, τ_s, τ_L, N_L) are taken from experimental recordings in macaque monkeys and typically differ for center and surround. *(Benardete and Kaplan, 1997, Visual Neurosci., Benardete and Kaplan, 1999, Visual Neurosci.)*

Decision Model

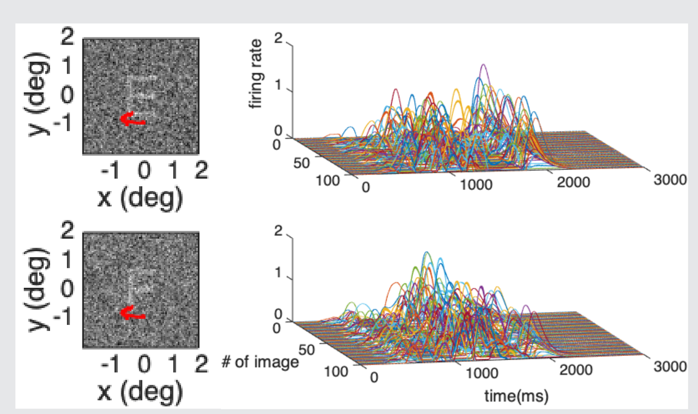


Fig 1. Firing rates of an M cell for an example FEM trajectory, with 100 examples of noise backgrounds.

Single neuron

$$p(S_k \mid r) = \frac{p(r \mid S_k)p(S_k)}{p(r)}$$

S: stimulus, r: response

Multiple neurons

- We assume neurons are conditionally independent
- Estimate the confusion matrix by evaluating the summation of log likelihood ratios of all cells

If r_i and r_j are the responses from two cells, the probability can be estimated as follwing:

$$p(r_i, r_j \mid S_k) = p(r_i \mid S_k)p(r_j \mid S_k)$$

log likelihood ratio of S_k vs. non S_k from all cells

$$\log\frac{p\left(S_k \mid \vec{r}\right)}{p\left(\sim S_k \mid \vec{r}\right)} = \sum_{n=1}^{N} \log\frac{p(r_n \mid S_k)}{p(r_n \mid \sim S_k)}$$

Main steps:

1. Reduce the dimensionality by principal component analysis (PCA)
2. Identify the optimal linear discriminator by Fisher discriminant
3. The decision is based on maximum a posteriori probability (MAP) computed by Bayes rule

RESULTS & NEXT STEPS

Performance of Individual Trajectories

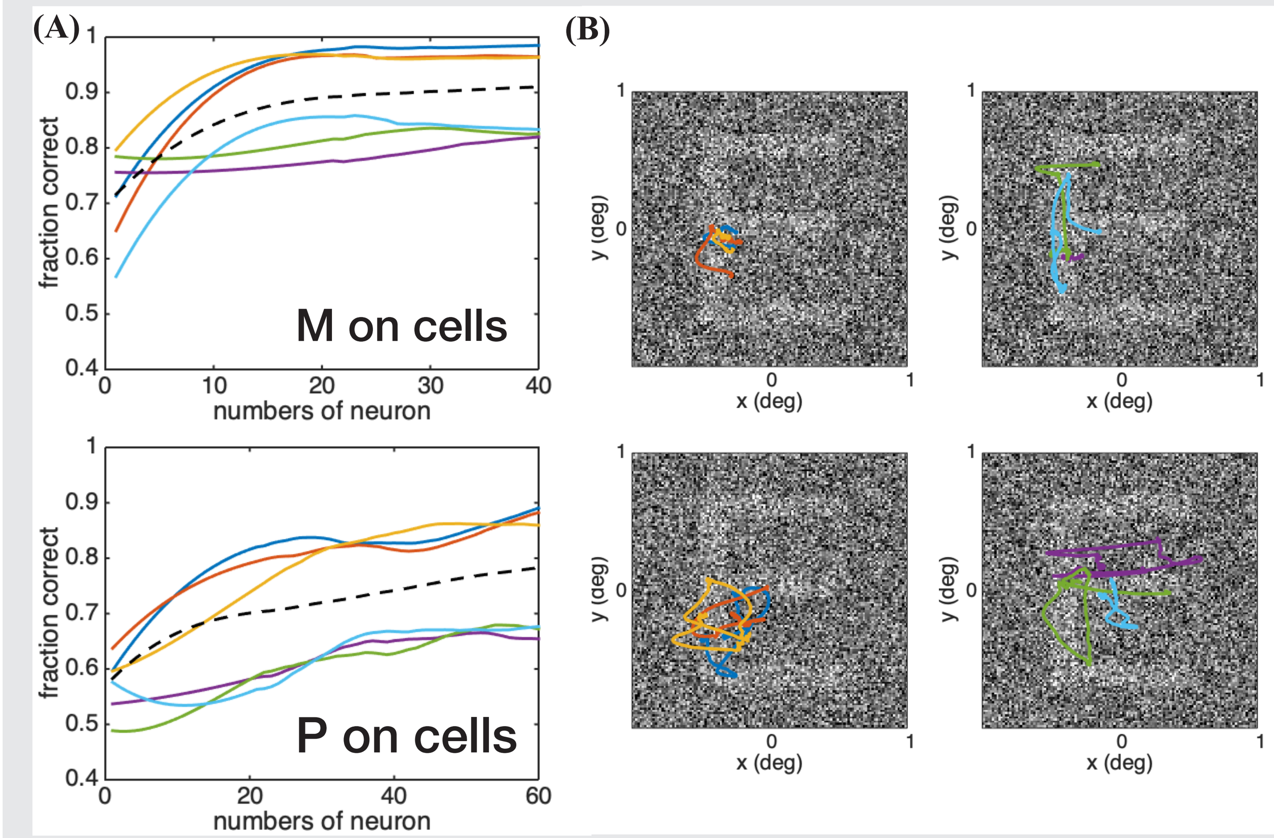


Fig 2. (A) Performance of individual trajectories. The mean performance of all trajectories are shown by the dashline in gray. (B) Example trajectories superimposed on the stimuli. The size of images are in 2 degrees.

Interim Conclusions

The model predicts trial-by-trial effect of FEM trajectories on performance. The benefit of specific trajectories are predicted to be substantial.

Next Steps

1. Experimental data collection to compare the experimental and modeling results
2. Investigate the charactistics of "good" and "bad" trajectories

Performance of individual cells and a population of cells

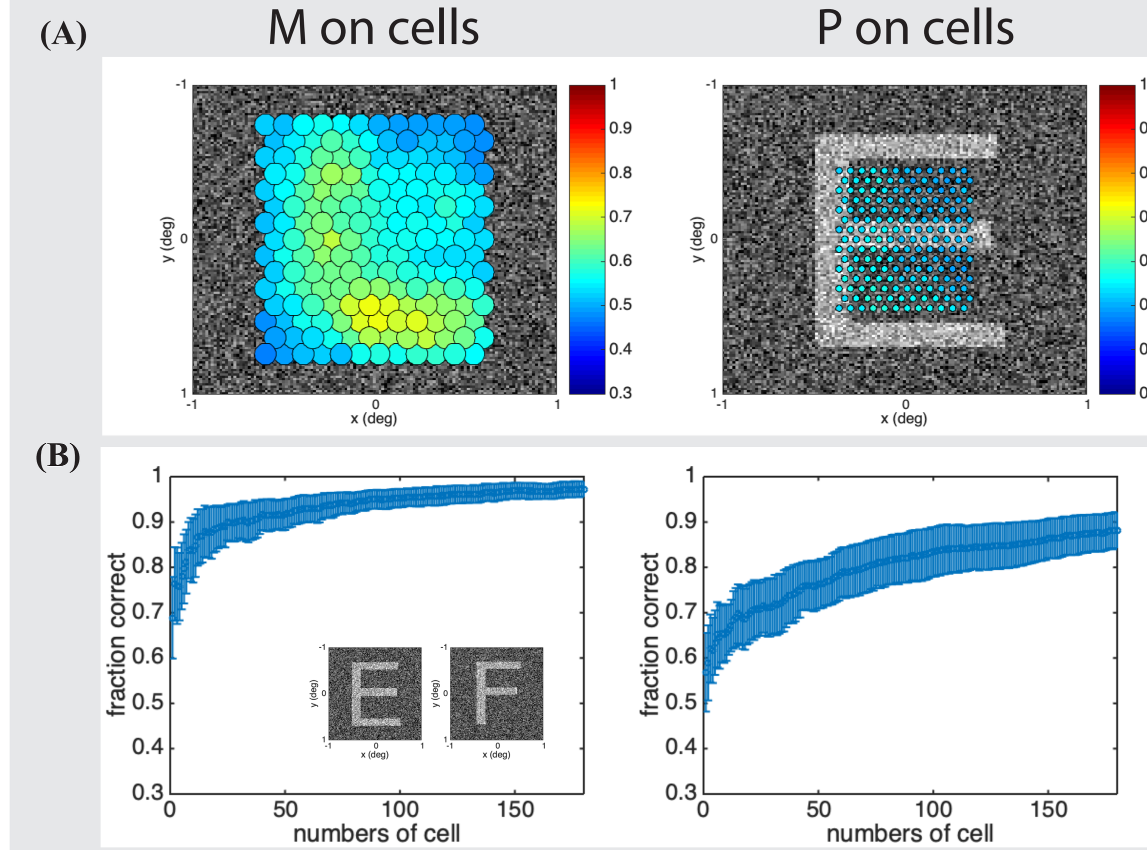


Fig 3. (A) Performance of letter E and F discrimination of individual cells. The colors represent fraction corrects. (B) The performance of the summation of a numbers of cells and its mean fraction correct and standard errors. Similar results was found when using different letter pairs.

Interim Conclusions

The model makes predictions about the retinal basis of performance based on (1) number of cells (2) cell types (3) cell locations

Next Step

Simulate with cell hybrids to determine the role of spatial and temporal differences between M and P cells in making use of FEM dynamics

Performance on Different Discrmination Tasks

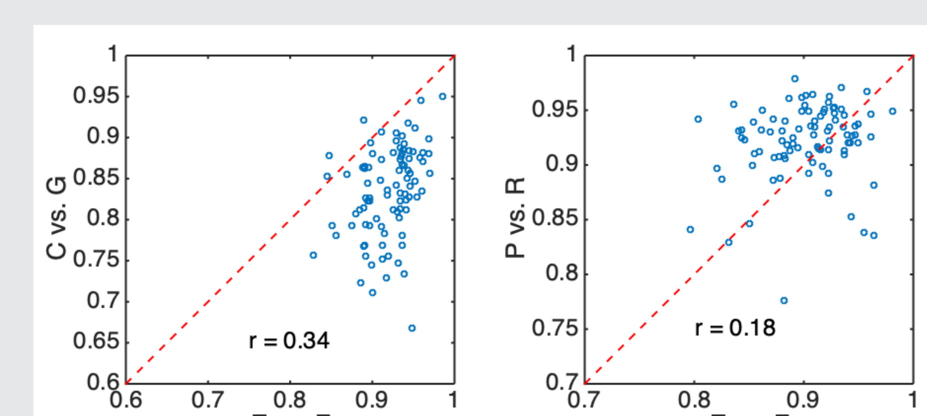


Fig 4. Scatter plots of the performance of different FEM trajectories while discrminating different letter pairs. Each dot represents the performance of one trajectory from a population of 30-50 randomly sampled M on cells.

Interim Conclusions

The benefit of specific trajectories are predicted to be task dependent.

Next Step

Experimental data collection to study whether control of FEMs would enable FEM trajectories to adapt to the visual task.