Learning receptor types from receptor responses

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Introduction

• Human color vision requires comparing responses of different types of photoreceptors.

• It is not known whether the underlying neural circuitry that implements these comparisons relies on molecular markers to distinguish responses from different photoreceptor types, or whether photoreceptors are typed via a learning process driven by the receptor responses.

• Here we ask whether it is possible to learn the spectral type of each receptor in a retinal mosaic.

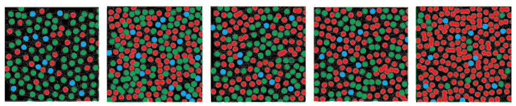

Figure 1. *Retinal mosaics.* Schematics of retinal mosaics from five individuals (Hofer *et al.*, 2005, Brainard *et al.*, 2008).

Algorithm & Methods

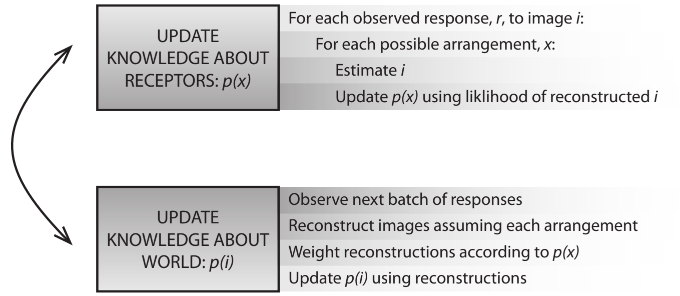

Figure 2. *Algorithm overview.* Images are successively presented to the model retina. Each observed response is used to update the estimated types of each receptor in the mosaic. The type estimates rely on knowledge about the parameters of the stimulus distribution, which are also unknown. These prior parameter estimates are updated after each batch of *n* stimuli. The prior parameter estimates rely on knowledge about the receptor types. Despite initial uncertainty, after many iterations, the algorithm will correctly tag receptors and estimate stimulus prior parameters.

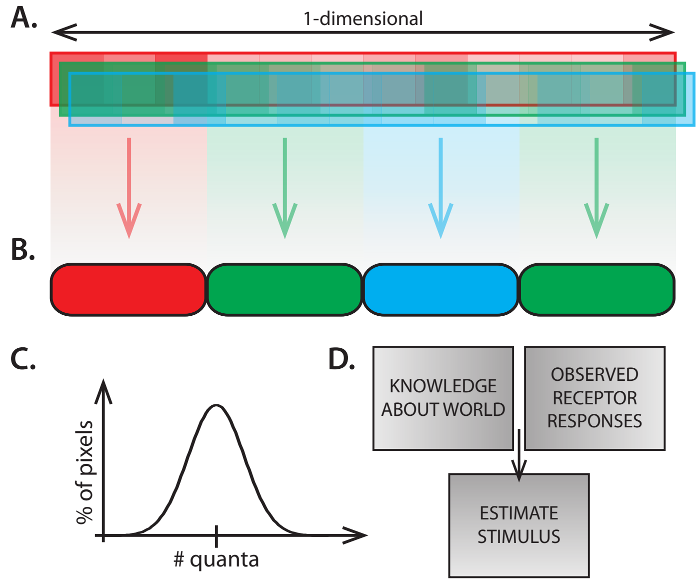

Figure 3. *Model overview.* **A.** *Model world.* Each image contains one intensity value per waveband at each of 12 pixels. **B.** *Model retina.* The optics blur the retinal image, which is then sampled by punctate receptors. Each receptor responds maximally to one of the three wavebands. **C.** *Stimulus distribution.* Stimuli are drawn at random from a multivariate Gaussian distribution. Here we illustrate a single dimension of the stimulus distribution. Parameters of the stimulus distribution include the waveband correlation and spatial correlation. **D.** *Estimating stimuli.* Given the current estimates of the parameters defining the stimulus distribution and the observed receptor responses, we use Bayes' Rule to estimate the stimulus that gave rise to the responses.

Results

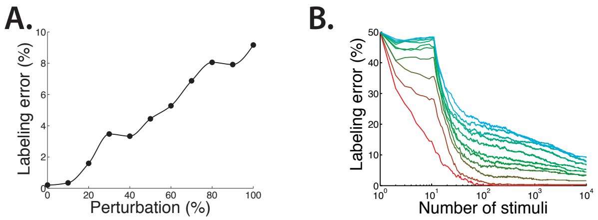

Figure 4. *Learning photoreceptor labels.* **A.** *Summary.* Here we assessed the mean labeling error after ten thousand stimulus draws as a function of the initial accuracy of the stimulus prior. **B.** *Learning over time.* We presented images to the model retina and measured the proportion of correctly tagged receptors after each stimulus draw. We also explored how accuracy of the prior knowledge about the world affects the accuracy of receptor typing. The red curve was generated using the true stimulus parameters as the prior, while the blue curve was generated using a randomly drawn prior.

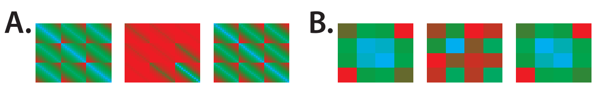

Figure 6. *Example matrices.* **A.** *Covariance estimates.* Here we show the true (left), prior (middle), and estimated (right) stimulus covariance matrices. **B.** *Response covariance estimates.* Here we show the matrices in A, viewed through the true receptor arrangement (shown in Fig. 3B).

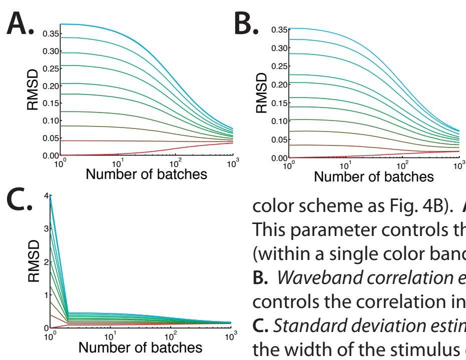

Figure 5. *Learning stimulus prior parameters.* We presented images to the model retina and estimated the parameters of the stimulus prior after each batch of 10 draws (same color scheme as Fig. 4B). **A.** *Spatial correlation estimates.* This parameter controls the correlation in intensity (within a single color band) across spatial location. **B.** *Waveband correlation estimates.* This parameter controls the correlation in intensity across wavebands. **C.** *Standard deviation estimates.* This parameter controls the width of the stimulus distribution.

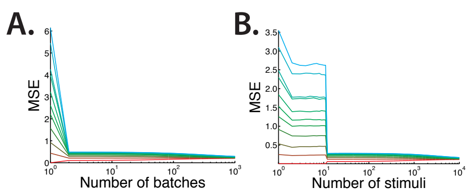

Figure 7. *Learning covariance matrices.* **A.** *Covariance estimates.* We measured the MSE between the true and estimated covariance matries after each batch of stimuli. **B.** *Receptor covariance estimates.* We measured the MSE between the true stimulus covariance matrix mapped through the true receptors and the estimated covariance matix mapped through the estimated receptors.

Conclusions

• Starting with a flat prior over receptor arrangements, our algorithm can correctly type each receptor in the retinal mosaic.

• Prior assumptions about stimulus statistics can affect the accuracy of the receptor typing.

• Our analysis shows that the neural circuitry underlying color vision need not rely on molecular markers to distinguish photoreceptor types.

• These computations address the fundamental question of the degree to which sensory systems can learn their front-end properties through experience.

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