Perceptual adaptation: Getting ready for the future

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Motivation

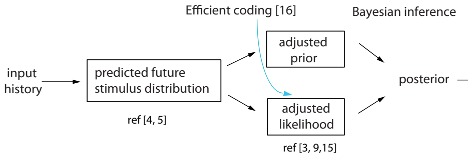
Adaptation is ubiquitous in sensory systems. It can express itself through various aftereffects [1]:
- change in discrimination threshold;
- perceptual biases.

It is commonly believed that these aftereffects arise from a mismatch between encoding and decoding (i.e., coding catastrophy [2]). Here we propose a new theoretical framework that unifies various ideas for a functional understanding of percpetual adaptation.

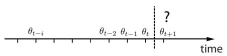
Key idea: The goal of adaptation is to prepare the perceptual system for the next sensory input.

-- Predicting the distribution for the next input based on input history.
-- Adjusting both encoding and decoding based on this distribution (matching decoding with encoding) .

Theoretical framework



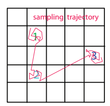
Predicting future stimulus distribution



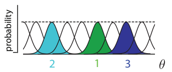
***Goal*:** Predicting $P(\theta_{t+1}|\ \theta_t, \theta_{t-1}, \theta_{t-2}, \ldots)$

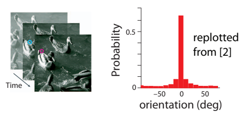
Hypothesis: Exploiting temporal regularities of the input.

A model of sensory input



Natural scene
piecewise smooth
[2, 17, 22]



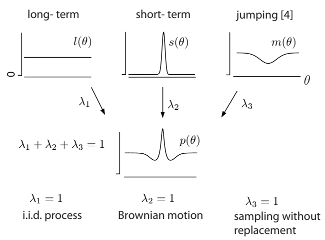


Visual sampling: local + jumping (saccades)

-- piecewise smoothness leads to an **increased** probability of future samples around the previous sample values.

-- Jumping to a new region (***self-avoiding*** [18]) leads to a **decreased** probability of future samples around the previous sample values.

Two sources of ingredients:
-- image: local smoothness + global discreteness
-- sampling: inhibition of return



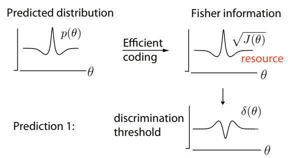
Cost function: $\underset{p(\theta)}{\arg\min} \sum_i \lambda_i D_{KL}(\ .\ ||p(\theta))$

$\longrightarrow\ p(\theta) = \lambda_1 l(\theta) + \lambda_2 s(\theta) + \lambda_3 m(\theta)$

Adaptation experiments :
λ_2 is large due to fixation, $s(\theta)$ is narrow;
$m(\theta)$ is deeper.

Natural viewing conditions :
λ_2 is smaller, $s(\theta)$ is wider;
$m(\theta)$ is more uniform.

Adjusting the sensory representation



For small Gaussian noise [6], maximizing information

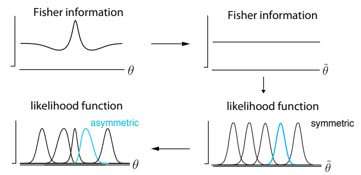
$$I[\theta, m] = \frac{1}{2}\ln(\frac{\int \sqrt{J(\theta)}d\theta}{2\pi e}) - D_{KL}(p(\theta)||c\sqrt{J(\theta)})$$

$\longrightarrow\ p(\theta) \propto \sqrt{J(\theta)}$ (also see ref [6, 7, 8])

i.e. allocating resource according to prior belief.

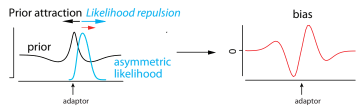
$\delta(\theta) \propto \frac{1}{\sqrt{J(\theta)}}$ (ref [14])

Adjusted likelihood (asymmetric)



Efficient coding leads to an asymmetry in the likelihood function, with a heavier tail ***away*** from the peak of the prior [9].

Bayesian observer model for adaptation



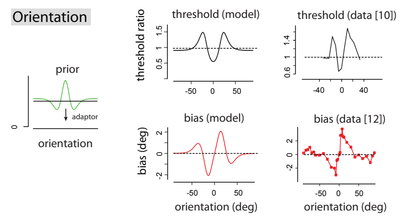
Prediction 2:

-- bias **away** from adaptor if stimulus is close to adaptor;

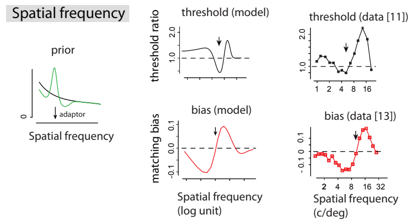
-- bias **toward** adaptor if stimulus is far away from adaptor.

Model vs. Data

Orientation



Spatial frequency



Conclusions

- A theoretical framework for perceptual adaptation:
  - predicting the future input distribution;
  - efficiently adjusting the sensory representation according to this distribution;
  - Bayesian inference based on efficient sensory representation.
- Predictions of perceptual biases and change in discrimination threshold well match the reported adaptation aftereffects (orientation & spatial frequency).

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