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Rapid dynamics in the retina

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Abstract

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1 Introduction

The visual system processes complex stimuli by extracting from the visual scene spatio-temporal features that are relevant to behavior. This means that different neurons at different stages of perception are sensitive to specific features of the visual stimulus. Pulling together information from all this different types of neurons, the brain is then able to reconstruct the visual perception. This feature extraction already happens at the level of retina gollisch$_e ye_2 010$.

Considered a part of the central nervous system in vertebrates, the retina is made of only a handful of layers of neurons. The first layer is composed of photo-sensitive neurons called photoreceptors, that act as light sensors for the network. They give their excitatory output to bipolar cells, which can be divided into 14 different types and each type responds differently to the same stimulus, allowing for a vast functional diversity. Bipolar cells excite in turn ganglion cells, which finally send the pre-processed visual information to the rest of the brain through the optic nerve. Ganglion cells can also be divided into different functional types (at least 32) and each type is believed to extract a different feature from the visual scene. The retina also has two classes of inhibitory neurons, horizontal and amacrine cells, that further modulate the

processing of excitatory cells. Compared to the rest of the brain, its relative simplicity and its relatively easy experimental accessibility make the retina an ideal neural tissue to study using computational models.

It has been shown that in order to operate optimally in a wide range of stimulation conditions, the retina adapts its responses to the statistics of the visual scene. In particular, it was observed to adapt both to the average luminance (stimulus average) and to the average contrast (stimulus distance from the mean or variance). The retinal adaptation to the luminance of the scene is somehow well understood. For instance, it is known that the retina uses different neuronal pathways at low and high luminance. Less attention was given to the contrast adaptation, and it was always studied through the use of simple stimuli. From previous studies, contrast adaptation is known to have different timescales. While slower contrast adaptation ($\approx\ 10s$) is better understood, fast adaptation (¡1s) is more complex to study, and it is still unclear how it affects temporal processing and the sensitivity to stimulus featuresbaccus$_{f}ast_{2}002.Furthermore, contrastadaptationcanalsohappenatdifferentscales, eitheratth$

In this work, we want to address how does fast contrast adaptation plays a role in natural scene processing.

2 Results

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3 Methods

Experimental design and data processing. The laboratory has access to two experimental rooms that enable state-of-the-art experimentation on the retina. From my point of view, it is a golden ticket to original and good quality data. I am learning how to retrieve multi-electrode

Figure 1: **Computation of local sensitivity.** Figure from goldin$_c ontext - dependent_2 022$**a**.$Naturalimagesareperturbedwithcheckerboards.Scalebar = 500\mu m.$ **b**. A random sequence of perturbed natural images is being flashed. A gray frame separates all flashes. To compute LSTA, we average all different perturbations weighed by the number of spikes they evoked. **c** An example of LSTA for a cell of the retina of a mouse. On top, the spatial and temporal receptive field of the cell, as classically used. On the bottom, the LSTA of the cell (right) for different natural images (left). A green ellipse fitted on the classical spatial field is shown on the LSTA for reference. **d** Same than c for an axolotl. Note that the stimulus shown here is slightly different from the one we use to trigger fast adaptation.

array experimental data, including semi-automatized spike sorting and cell typing. This process can take up to an entire day for a single experiment. I am also able to share my programming skill to help and improve the data pipeline of the laboratory. This part of my project includes design of experimental stimulus, trustworthy sanity checks and high quality data visualization.

To study fast adaptation, we use a simple stimulus consisting of an adaptation frame (either gray or a checkerboard or its inversion) followed in 400ms by one of three handpicked natural images. Each pair is repeated 1000 times. But each time, the natural images are slightly perturbed using a random checkerboard pattern. This enables the computation of the selectivity of the cell specifically on a local point of a stimulus space containing the natural image of interest (Figure **??**). We refer to it as LSTA goldin$_c ontext - dependent_2 022.Oneofthechallengehereistobeabletoide$

Modeling. This should be the main part of my internship and also the most challenging. We are designing a dynamical model of the retinal fast adaptation. In fact, we mostly look at the evolution of the response from an image to another, meaning that the dynamic we observe only spans two points in time. This reduction makes the model more realistic to study. Most of this job can be summarized as model design, python programming, sensitivity analysis and data fitting. By comparing how different modeling strategies reproduce the observed LSTA in the

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Figure 2: **Quick sketch of a gain control LNLN model.** Each bipolar cell is composed of a linear spatial filter that selectively respond to a part of the scene, a non-linear activation function, and a gain control mechanism that scale its output depending on past events. They all converge into on bipolar cell (forming its own receptive field) of which output is also modeled using a non-linear function.

data, we can gain insight on how fast adaptation to natural scene is implemented in the retina.

Our baseline model is the LNLN model of ganglion cell widely used in the literature. Each neuron is encoded as a spatial linear filter chained with a non-linearity (usually an activation linearity in the like of ReLU). A single layer of subunit neurons, representing bipolar cells, converge into a single modeled ganglion cell. We would like to add temporal dynamics to this model, either by adding a time dimension to the spatial liner filter of the cells or by considering a gain control mechanism. This last mechanism consists in scaling up or down the present output depending on past outputs (Figure **??**) chen$_alert_2013$.

We will first study our models in a data agnostic manner and study its behavior for different set of parameters. We will then fit it on our own experimental data using an efficient optimization framework in python using strategies developed in the field of machine learning.

Learning about the field. Finally, One of my main goal is to learn about the retina and its modeling. To that end, I am doing an extensive study of the literature to build my own library and also get to know the main theories and actors of the field. Through my internship, I also attend the lab weekly science meeting, the lab theoretical journal club as well as some exterior talks in Paris and its area. Finally, I will be attending the main yearly research congress about the retina around the end of my internship. It is called ERM and will be hosted in Tübingen, Germany.

References

Acknowledgments

Include acknowledgments of funding, any patents pending, where raw data for the paper are deposited, etc.

Supplementary materials

Materials and Methods

Supplementary Text

Figs. S1 to S3

Tables S1 to S4

References *(4-10)*