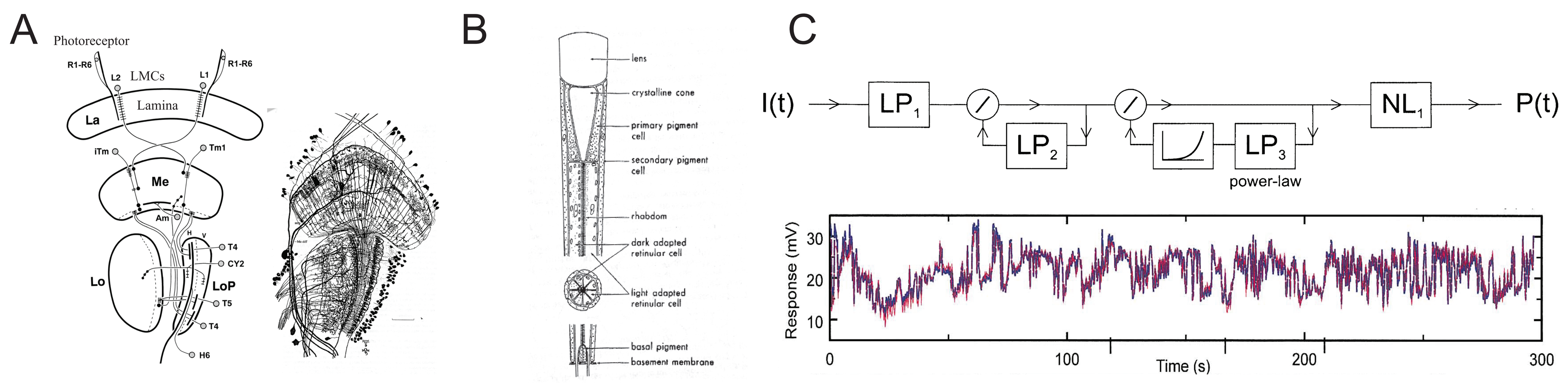
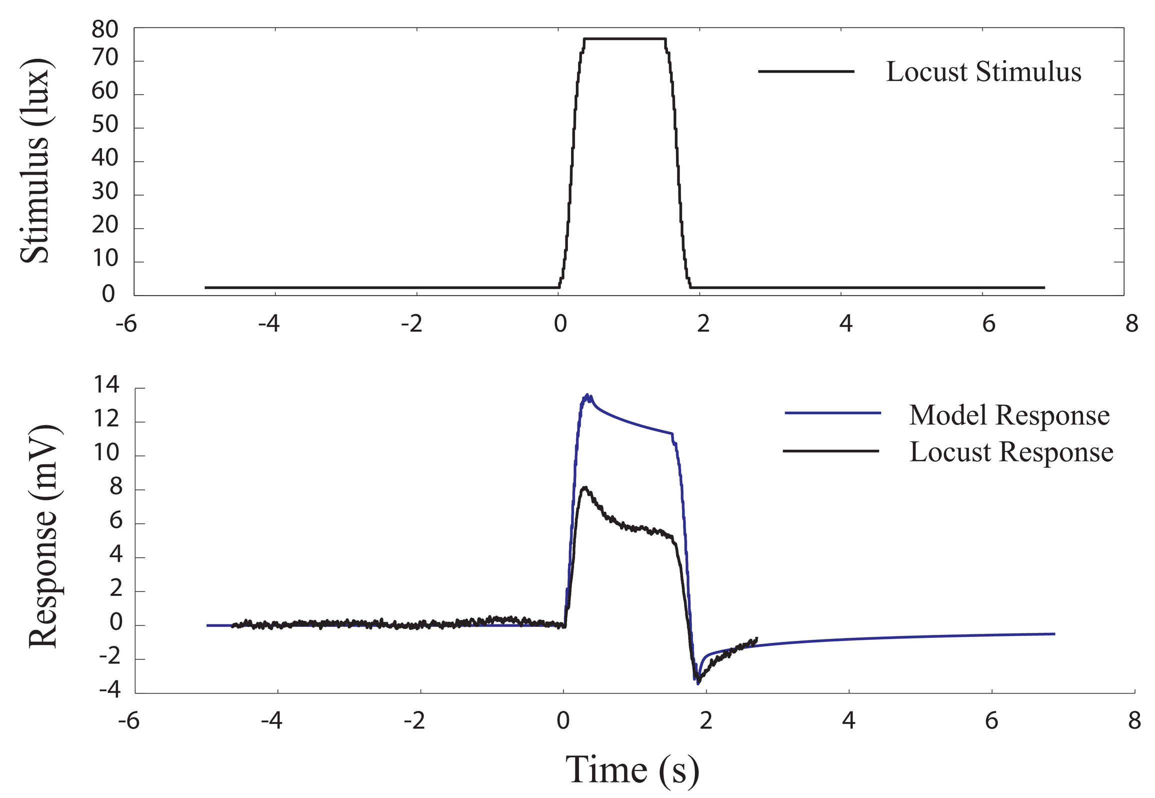
Nonlinear Modeling of Locust Photoreceptors

Jung Uk Kang, Department of Computer Science, Brown University, Providence RI 02912
Advisor: Fabrizio Gabbiani, Department of Neuroscience, Baylor College of Medicine, Houston TX 77030

Introduction



The visual systems of animals have long been studied as models of how the neural circuits process information. This is because individual cells throughout the system can be recorded and their responses related to the light input presented. Photoreceptors, the cells responsible for transducing incident light energy into neural signals are the first stage of this system. A schematic drawing of the insect visual system is shown in A, and a detailed sketch of a photoreceptor is shown in B. How insect photoreceptors respond to a wide range of light intensities and patterns has been well characterized over the years, and detailed models describing these responses have been developed. One particularly successful model was developed by Hans van Hateren and colleagues (van Hateren and Snippe 2001) based on responses from fly photoreceptors. This model describes the membrane potential fluctuations resulting from external luminance changes over 3 orders of magnitude using several sequential nonlinear filtering steps. The second stage of processing, Large Monopolar Cells (LMCs) in the lamina have also been well studied, and have also been successfully modeled using nonlinear-linear-nonlinear (NLN) cascade model (Juusola et al, 1995). The structure of the photoreceptor model and the response produced by the model are presented above in figure C. LP stands for Low-Pass filter, and NL stands for Non-Linear filter. LP1 and LP2 has tau1 and tau2 as its parameter respectively. LP3 has a two parameters k1 and k2. The output of LP3 is k1exp(k2*input).



With the parameter values (tau1 = 1. 69; tau2 = 71.8; k1 = 0.689; k2 = 9.07) for fly photoreceptor, the output of the model did not match with the actual data from photoreceptors. The actual response of a locust photoreceptor and that of the van Hateren model with default parameters is shown above.

Goal

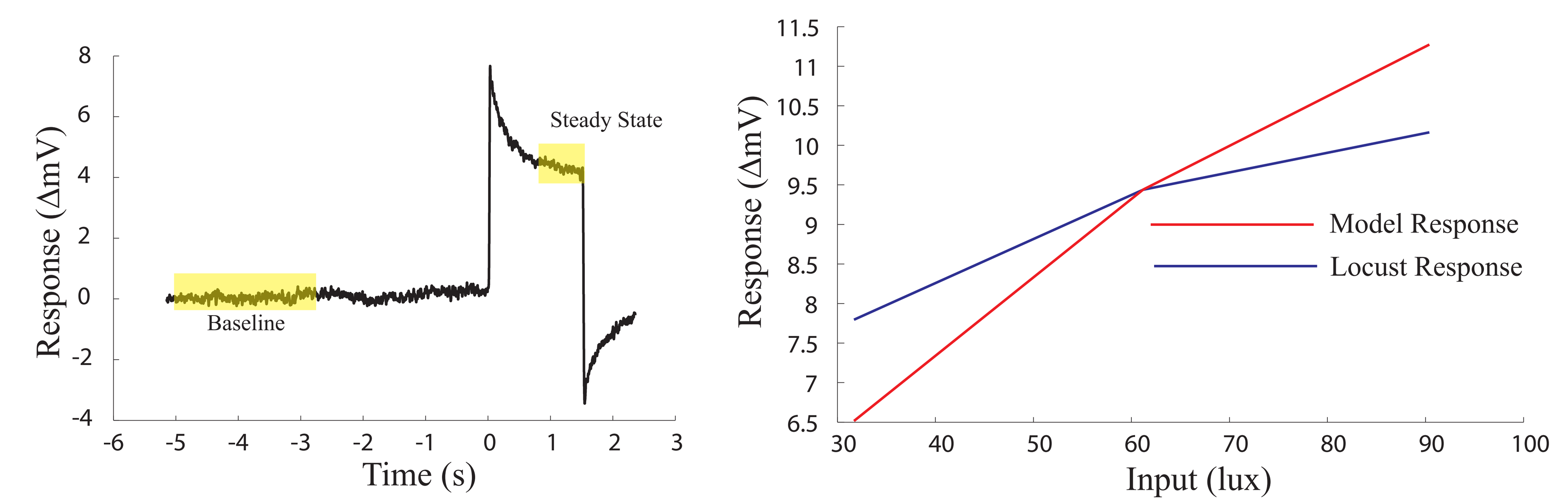
The goal of this project was to adapt existing models of early visual processing in flies, the van Hateren photoreceptor model and the NLN cascade LMC model, to fit the responses of locust photoreceptors. This will allow the Gabbiani laboratory to run large-scale simulations of higher order visual processing in the locust visual system using the outputs of these models as realistic neural inputs.

Finding the Best Model Input

The van Hateren model was developed using data that was not calibrated with regards to the absolute light intensity. Thus, we needed to find the best linear transform to match the light intensities used during the photoreceptor recordings (Iexp) to the corresponding range of model input values (Imodel). Since all we had to use were photoreceptor responses, we decided to fit the linear function

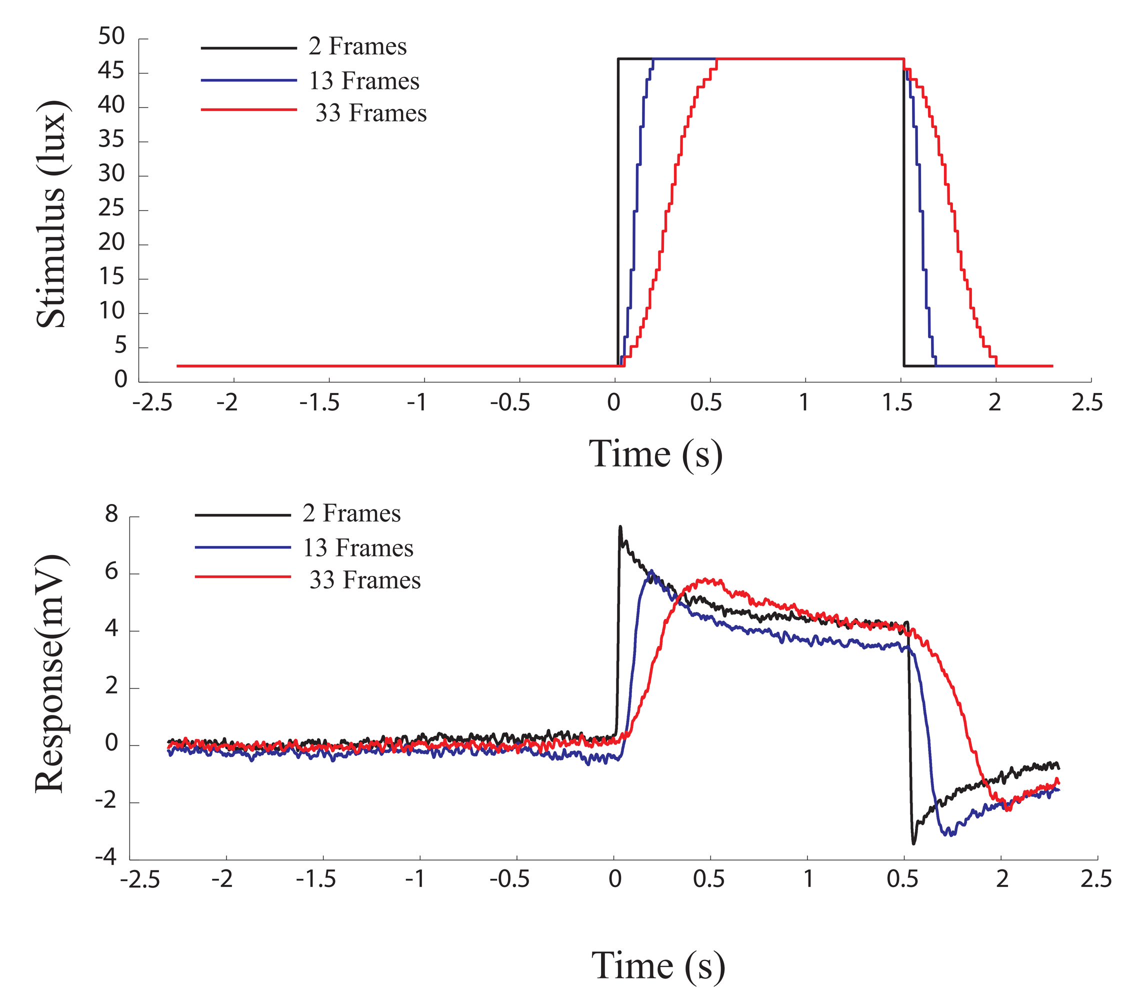
$$I_{model} = A \cdot I_{lux} + B$$

by minimizing steady state response magnitudes of the van Hateren model and the data for 3 different stimulus intensities. The fitted values of A and B returned to be 16.1738 and 186.6813 respectively.



There were three input values (31.7, 61.2 and 90.4) to observe, and the differences between the model response and locust response were 1.2801, 0.0020, and 1.1096 respectively.

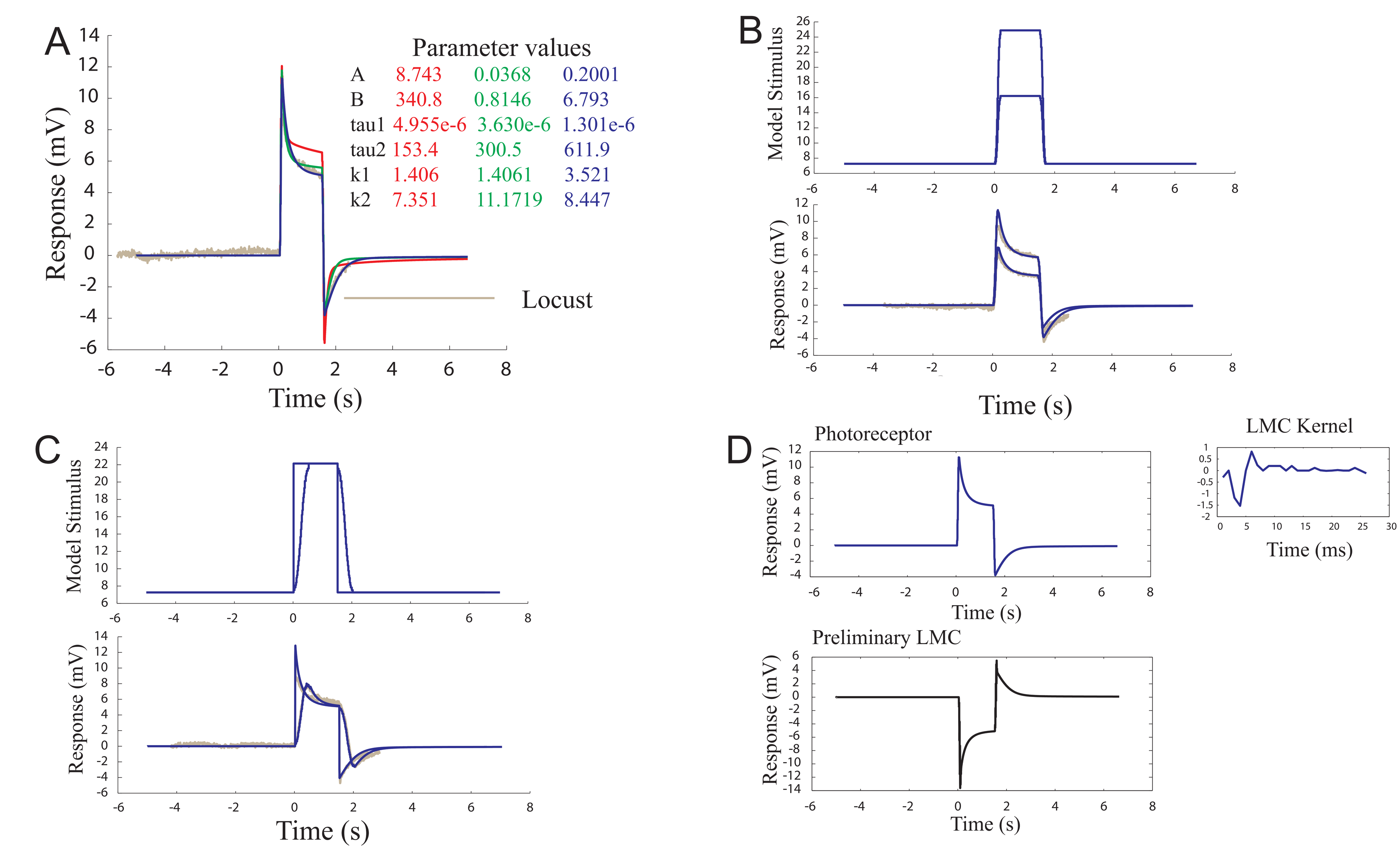
Locust Photoreceptor Responses to Luminance Changes



Above is an example of the locust photoreceptor responses that we used to fit the model. Luminance pulses that increased and decreased at different speeds were presented while recording the membrane potential of a single photoreceptor. Stimulus traces are shown on the top, and recordings below. One can see that the response speed of photoreceptor tracks that of the stimulus change. One stimulus frame equals 1/60 sec.

Fitting the Model

After finding the best fit luminance transform while keeping model parameters constant, we needed to fit the 4 model parameters (tau1, tau2, k1, k2). We first tried to freely vary all 6 parameter values (model parameters plus A, B), but that didn't converge to a solution, and the end parameter values didn't yield good fits to the data (red line). We also tried to hold the parameters k1 and k2 constant, thinking that these govern responses over longer timecourses than the stimuli were presented, but the solution arrived at was clearly not a good fit (green line). After limiting the algorithms iterations to 300, but changing start conditions, we found a reasonable solution, shown in blue. It took 7 hours on average to obtain each set of parameters in panel A. These fits are shown for multiple stimulus brightnesses (panel B) and speeds (panel C) to show that they fit the range of experimental data well.



Sum of square of residuals: Red 2.6475e+04 mV² Green 2.5749e+04 mV² Blue 1.4135e+04 mV²

We also started to implement the NLN model of LMCs, but were limited by time and lack of quality recordings against which to fit the model. We implemented the linear filter stage of the model, which produces responses that are inverted and emphasize transient portions of the response when compared to photoreceptor output. This is shown in panel D.

Conclusions

We were able to adapt a nonlinear model of fly photoreceptors to locust photoreceptor responses.

We began implementing a model to describe the filtering properties of Large Monopolar Cells (LMCs).

References

Juusola et al (1995) Nonlinear Models of the First Synapse in the Light-Adapted Fly Retina Journal of Neurophysiology 74: 2538-2547
Mah et al (2008) Implementation of an elaborated neuromorephic model of a biological photoreceptor Biological Cybernetics 98: 357-369
van Hateren and Snippe (2001) Information theoretical evaluation of parametric models of gain control in blowfly photoreceptor cells Vision Research 41: 1851-1865

Acknowledgements

I would like to thank Fabrizio Gabbiani and Peter Jones for their mentoring.
This work was partially supported by NSF REU Grant DMS-0755294.