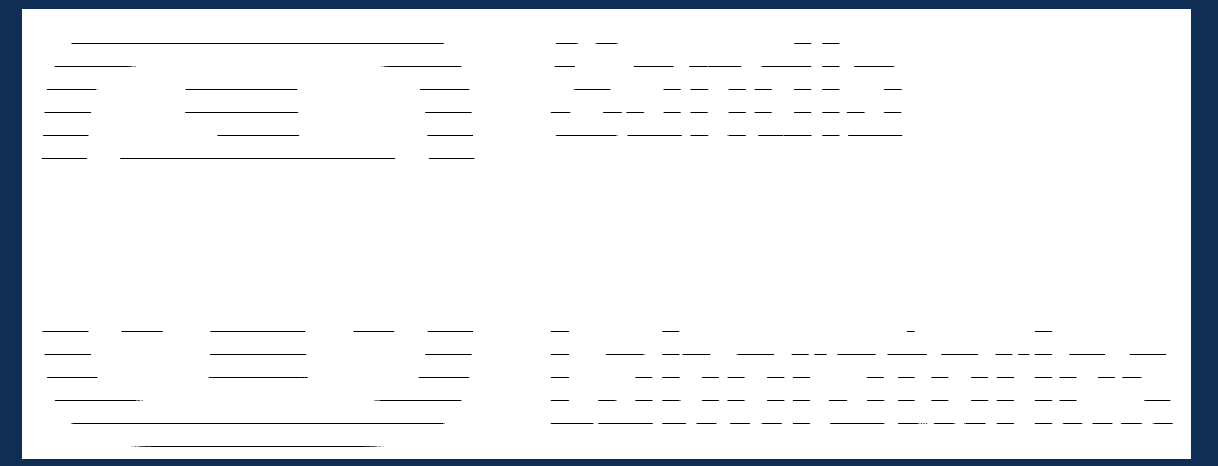


Retinal-Inspired Algorithms for Motion Detection

Frances S. Chance and Christina E. Warrender



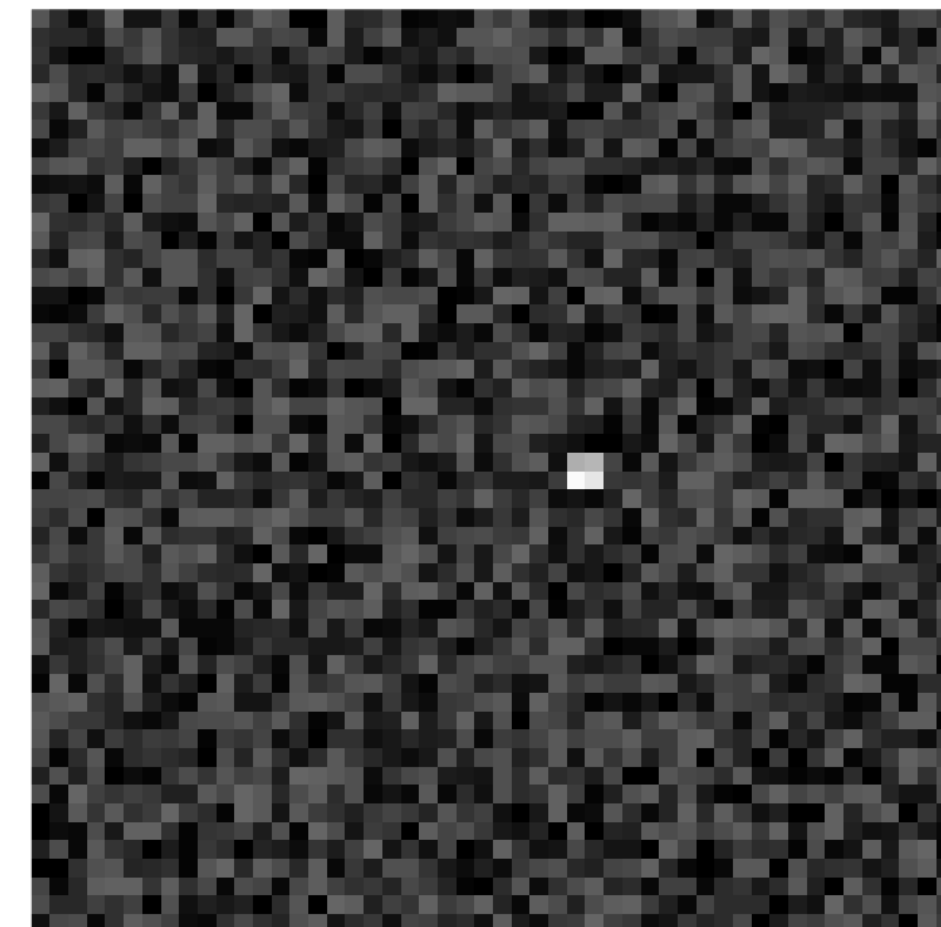
Abstract

A major challenge facing detection systems is detecting signals-of-interest in noisy backgrounds. The difficulty of this task is amplified by advances in sensor sensitivity and additions of multiple sensor modalities into the detection system. Modern detection systems must therefore have the capability to handle an ever-increasing diversity of “clutter” or “distractor” signals. While retinal circuitry may appear simple compared to higher-level areas of the brain, the retina contains a surprising diversity of retinal cell types (detecting motion, color, etc.) that perform an equally wide range of computations to “preprocess” visual input for transmission through the information bottleneck of the optic nerve. Our research focuses on understanding the algorithms employed by the retina (the sensor of the visual system) and how these algorithms may be adapted to improve modern detection systems

Model Overview

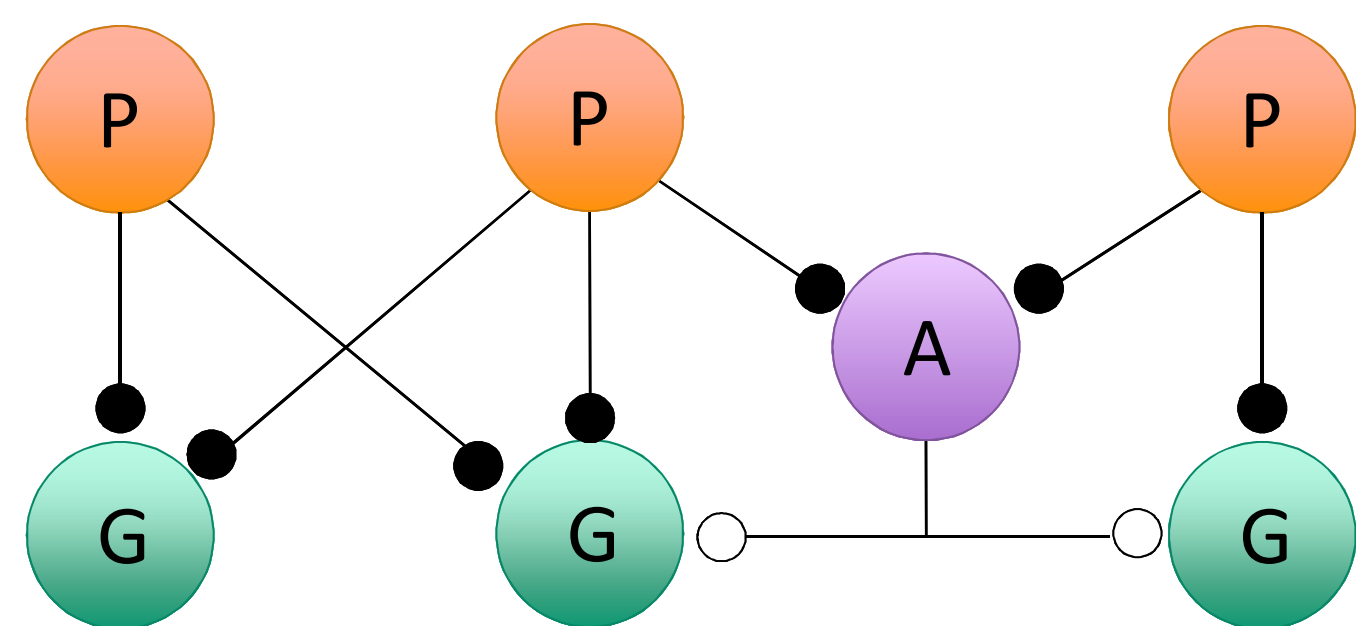
We seek to evaluate and compare strengths and weaknesses of different models of motion-sensitivity in retina.

For this study we consider the simplest possible circuit that captures characteristic features of each motion-sensitive model. For this purpose only, horizontal cells and bipolar cells are not included in this study.



Example stimulus: 2x2 target against a lower-luminance noisy background

Generic circuit



Photoreceptor/Pixel

$$P_i = [I_f - I_{f-1}]_+$$

For pixel i , photoreceptor response (P_i) is proportional to the change in luminance (relative to the previous frame). For this study, only ON-photoreceptors are incorporated (P_i is rectified).

Amacrine Cell

$$A \sim \sum_i w_i P_i$$

Amacrine cells mediate lateral interactions between ganglion cells.

In the circuit above, the amacrine cell (A) integrates input from two photoreceptors and sends input to ganglion cells. In the example above, ganglion cells receive inhibitory input (open circles) from the amacrine cell.

Ganglion Cell

$$G \sim \sum_i g_i P_i + \sum_i h_i A_i$$

Ganglion cells integrate input from amacrine cells and photoreceptors. Amacrine cell input may be either excitatory or inhibitory (although only inhibitory inputs are drawn above).

Motion-Sensitive Models

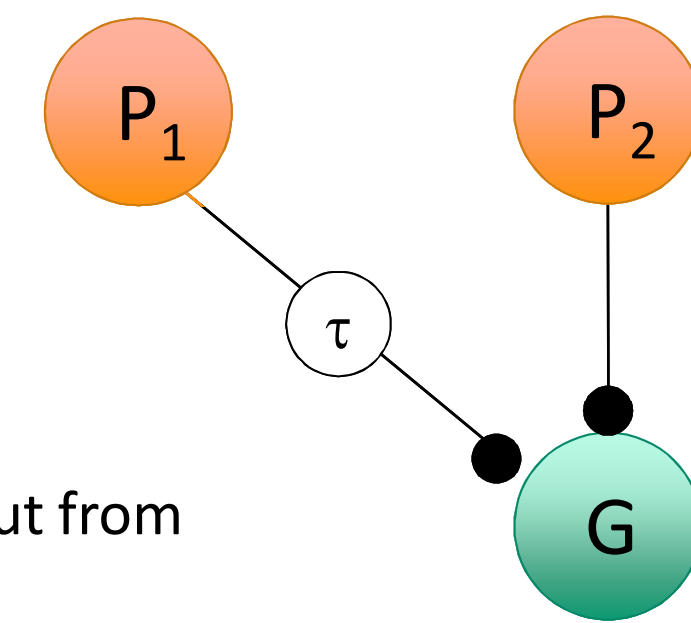
Reichardt Detector

We first consider the Hassenstein-Reichardt- (half)-detector (see Hassenstein & Reichardt 1956).

The Reichardt-detector ganglion cell receives input from spatially-offset photoreceptors. Input from one photoreceptor is temporally-delayed.

$$G_R = P_{1,f-\tau} * P_{2,f}$$

For the examples shown here, the ganglion cell integrates input from P_1 with a delay τ relative to input from P_2 . τ is chosen to be equivalent to the time it takes the target to move one pixel. In the figure above, the ganglion cell will be selective for targets moving left to right.

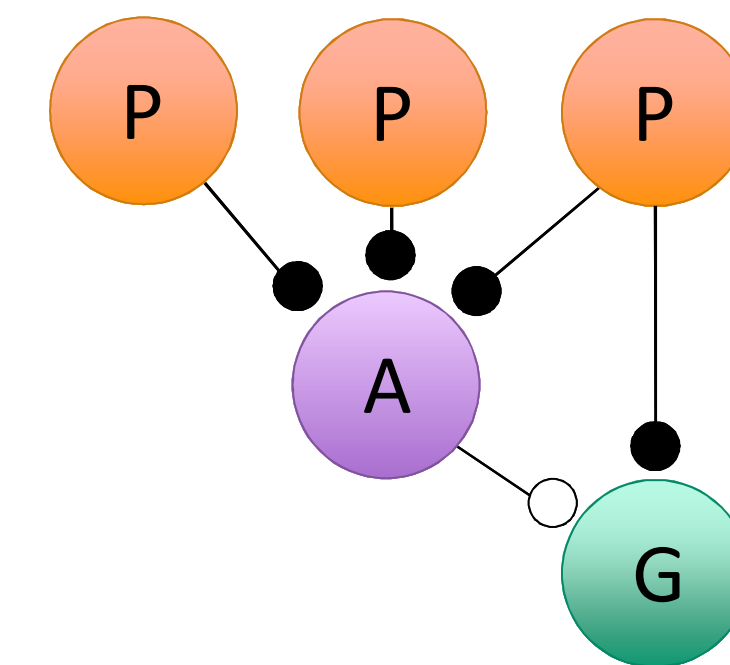


Object-Motion-Sensitive (OMS) Cells

We base our OMS model on previous work by Baccus et al (2008). Here the amacrine cell A integrates across all photoreceptors, essentially acting as a global change detector.

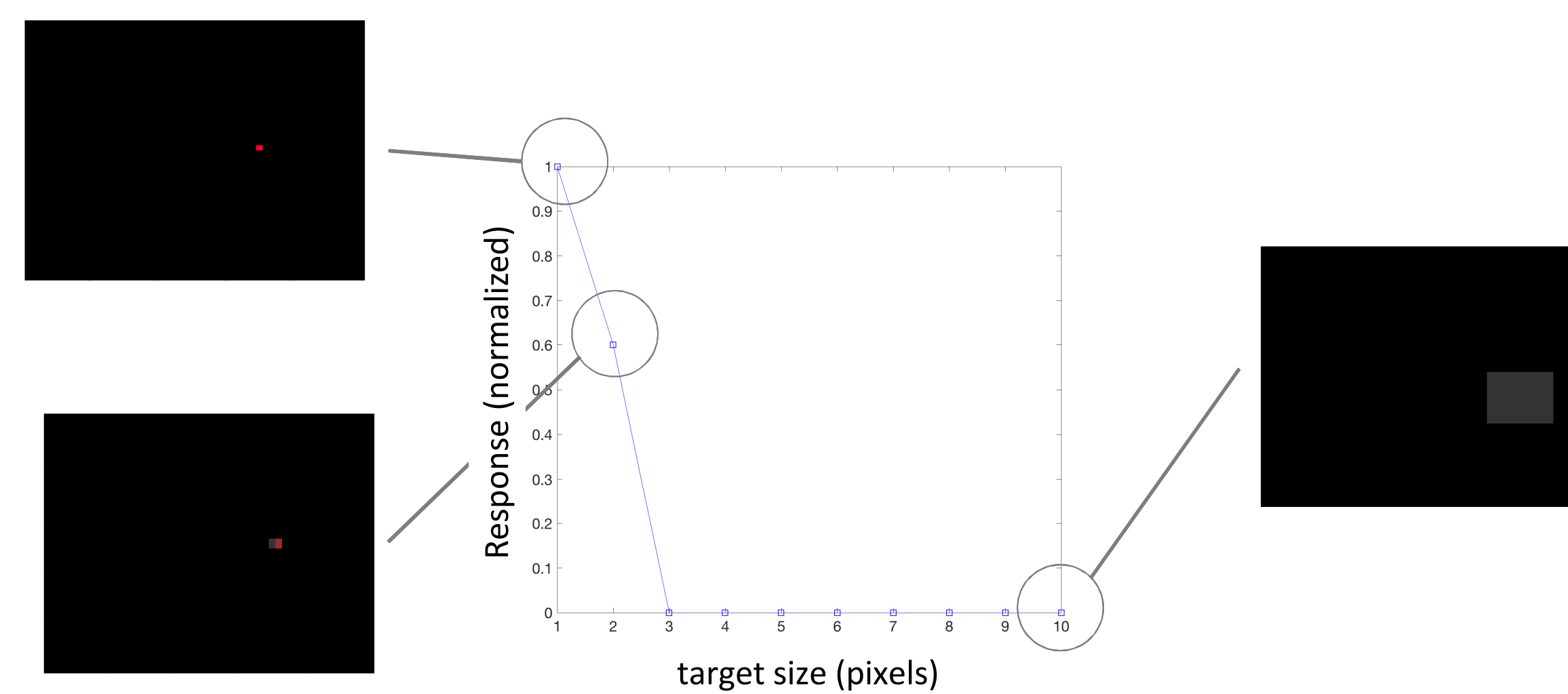
$$A = w \sum_i P_i$$

In this configuration, the amacrine cell (A) suppresses all ganglion cell responses whenever the level of synchronous input is sufficiently high.



Lateral Interactions and Target Size Tuning

Restricting amacrine cell interactions to be more local to ganglion cells effectively implements lateral inhibition. A richer lateral-interaction profile may be achieved by including excitatory amacrine cells as well as inhibitory cells.

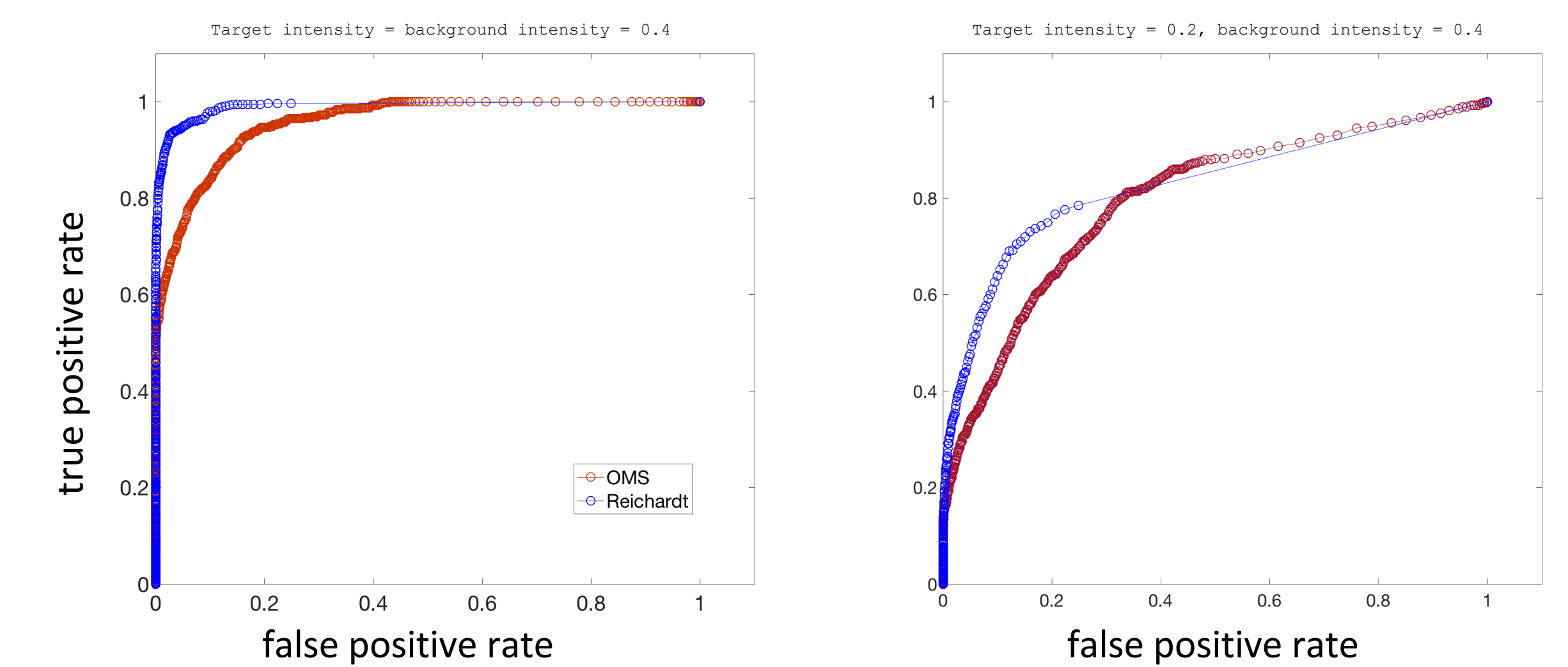


Lateral interactions (specifically local lateral inhibition above) can determine tuning for target size. In this example, lateral inhibition suppresses responses to larger targets.

Insets are stimulus regions close to target. Model ganglion cell response is overlaid in red.

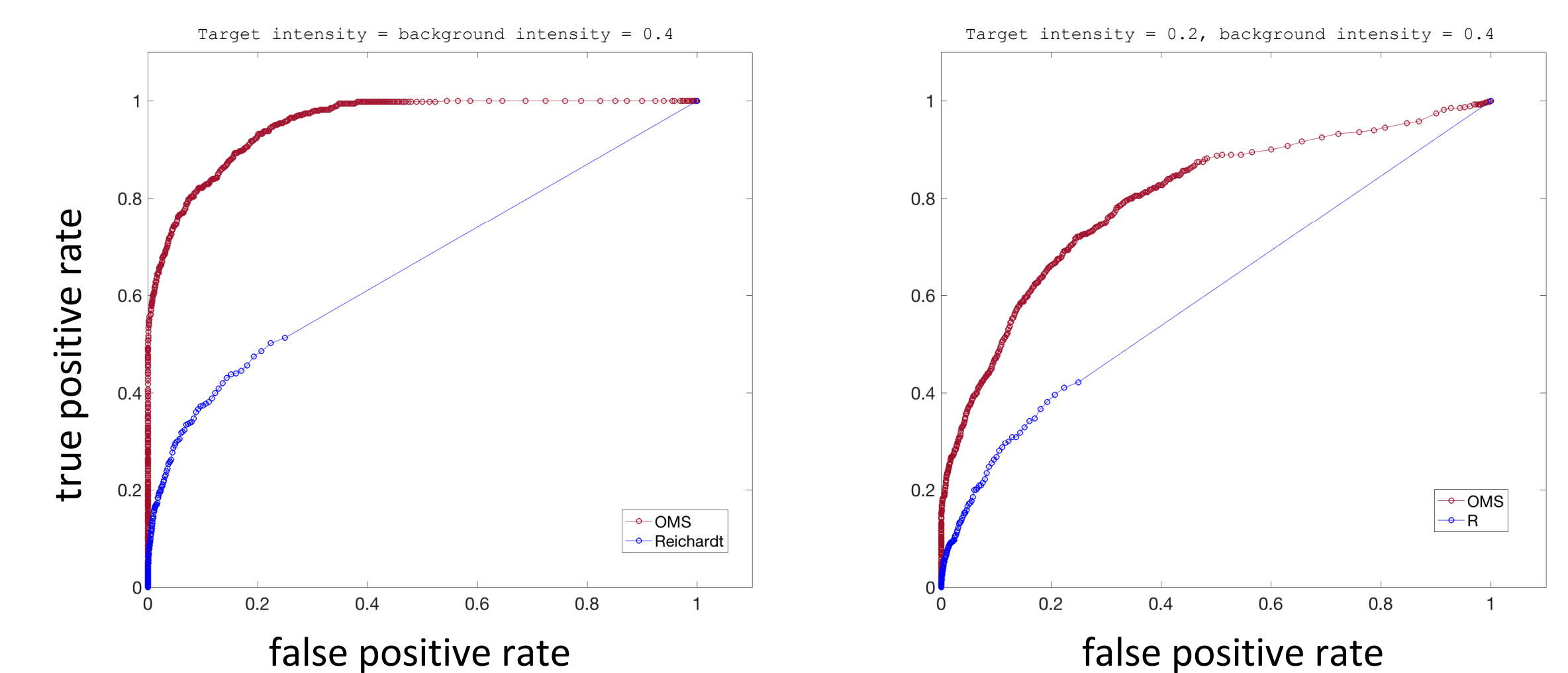
Reichardt Model is more robust to white noise clutter

White noise generates a significant global signal, which in turn drives significant amacrine-cell-mediated suppression of ganglion cells in the OMS model. For this reason, Reichardt detectors perform better than OMS cells at detecting motion in the presence of white noise.



OMS Model is more robust to varying target speeds

Reichardt models are known to demonstrate sensitivity to target velocities. In the figures below the target direction was left unchanged but the velocity was doubled. In this scenario, the input delay from the first photoreceptor to the ganglion cell is no longer cancelled by the spatial offset of the receptive field, and performance of the Reichardt model suffers relative to the OMS model.



We are currently incorporating additional biological realism to this implementation of the Reichardt model to address this vulnerability.

References

- Arenz A, Drews MS, Richter FG, Ammer G, Borst A (2017) Current Biology 27: 929-944.
- Baccus SA, Ölveczky BP, Manu M, Meister M (2008) J. Neuroscience 28: 6807-6817.
- Barlow HB, Levick WR (1965) J. Physiology 178: 477-504.
- Haag J, Arenz A, Serbe E, Gabbiani F, Borst A (2016) eLife 5: e17421.
- Haag J, Denk W, Borst A (2004) Proceedings of the National Academy of Sciences: 16333-16338.
- Hassenstein B, Reichardt WZ (1956) Z. Naturforsch. 11b: 513-524.
- Mauss AS, Vlasits A, Borst A, Feller M (2017) Annual Review of Neuroscience 40: 211-230.

Retinal-Inspired Algorithms for Motion Detection

Frances S. Chance and Christina E. Warrender



Abstract

A major challenge facing detection systems is detecting signals-of-interest in noisy backgrounds. The difficulty of this task is amplified by advances in sensor sensitivity and additions of multiple sensor modalities into the detection system. Modern detection systems must therefore have the capability to handle an ever-increasing diversity of “clutter” or “distractor” signals. While retinal circuitry may appear simple compared to higher-level areas of the brain, the retina contains a surprising diversity of retinal cell types (detecting motion, color, etc.) that perform an equally wide range of computations to “preprocess” visual input for transmission through the information bottleneck of the optic nerve. Our research focuses on understanding the algorithms employed by the retina (the sensor of the visual system) and how these algorithms may be adapted to improve modern detection systems