Breaking Symmetries in Attentional Modulation Models of the Visual Cortex

Dawn Paukner , Brent Doiron
University of Wisconsin - Eau Claire, University of Pittsburgh

Background

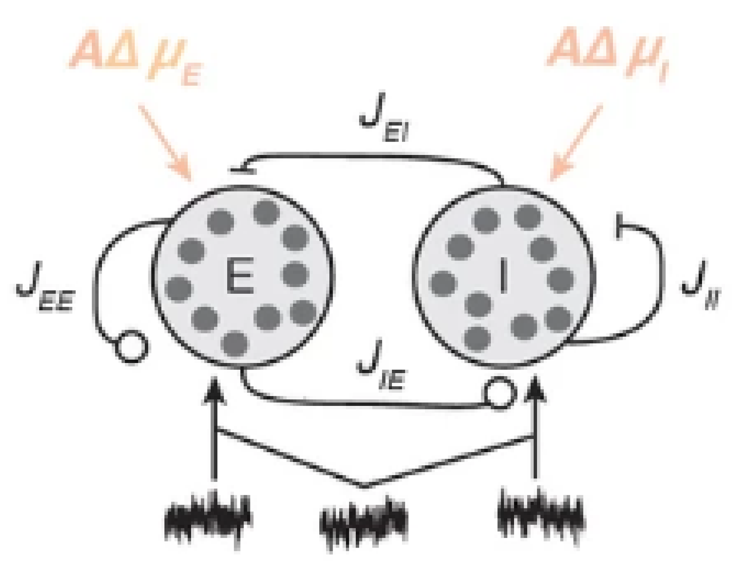

Figure 1: Excitatory and Inhibitory populations receive input from themselves, the other population, and external noise

In order to better understand circuit mechanisms involved with noise correlation and its dependence on the neural state, recordings during a visual attention of neural activity in V4 of the visual cortex of rhesus primates have been recorded and analyzed [1]. Previous models in the Doiron lab have predicted top-down input, such as attention, mainly impacts inhibitory neurons in V4 [2].

The previous model assumed symmetry in coupling strengths of excitatory and inhibitory populations of neurons. $J_{\eta,\theta}$ describes the coupling strength from population θ to population η (Figure 1).

$$J_{EE} = J_{IE} \equiv J_E \text{ and } J_{II} = J_{EI} \equiv J_I$$

The current project breaks this coupling symmetry by setting $J_{IE} = \alpha J_E$ and $J_{II} = \beta J_I$ where $\alpha, \beta \neq 1$

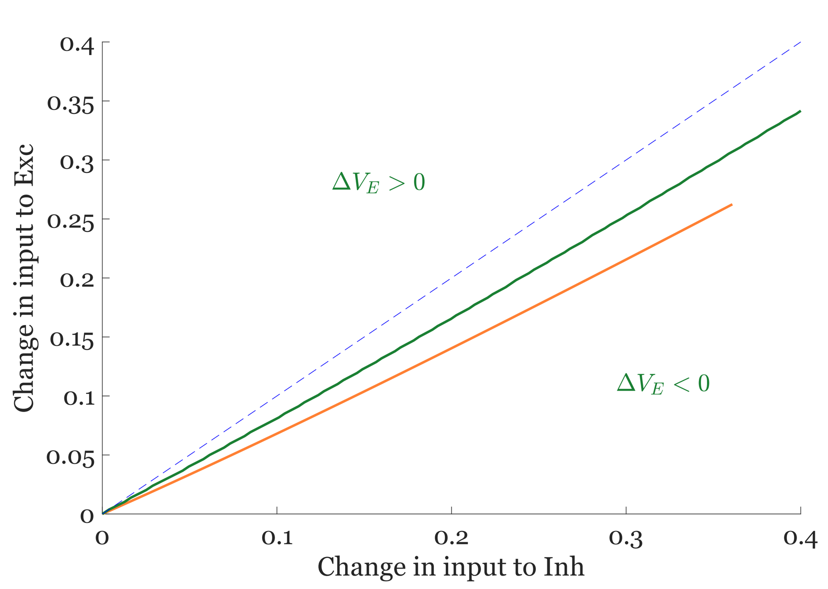

Figure 2: Spanning across rates of both populations changes the input to both populations. The orange line shows the change in variance along the attentional path. The green light shows where there is no change in variance.

Changes in Coupling Strengths Affect Changes in Variance

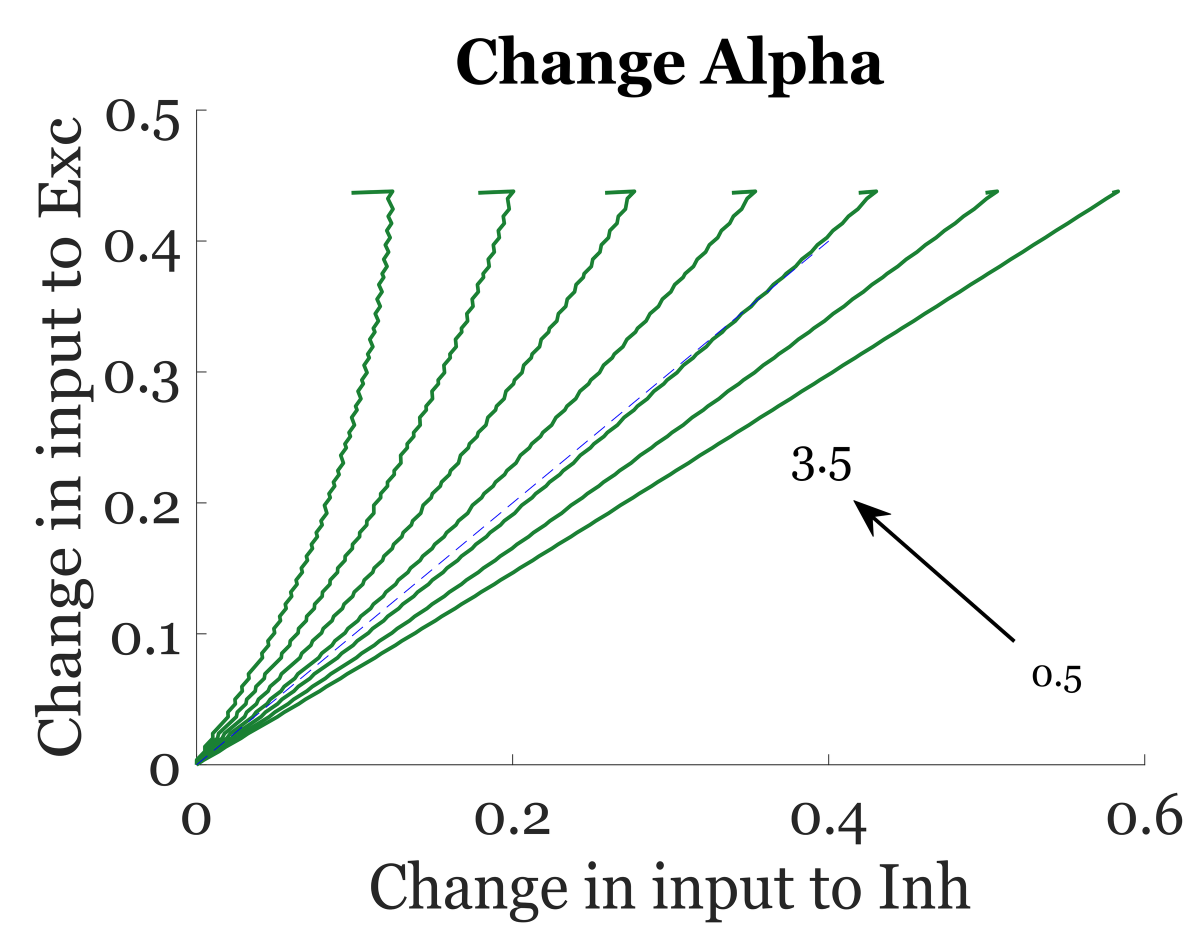

Figure 3: As α changes from $.5$ to 3.5 in steps of $.5$, the area containing $\Delta Var < 0$ increases. With the increased area, there is space where ΔVar decreases with attention, but affects excitatory input most.

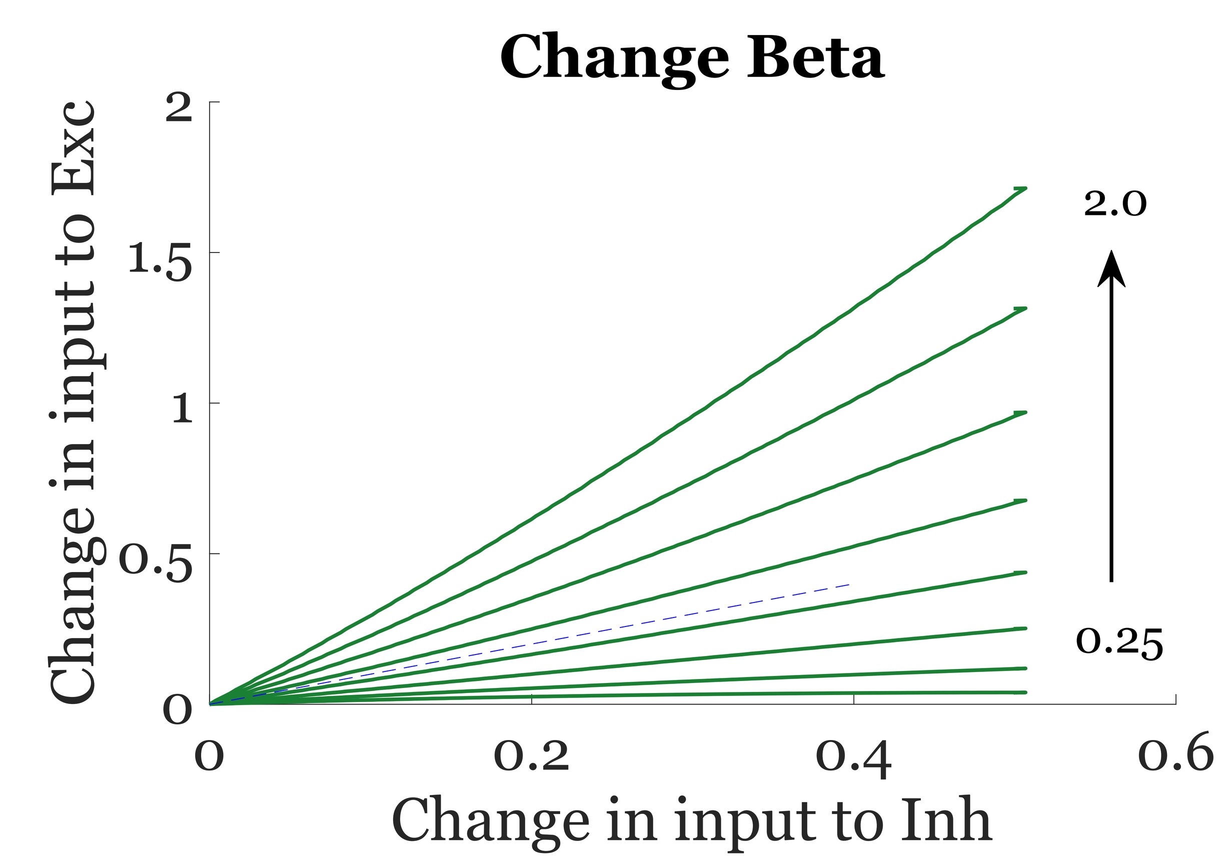

Figure 4: As β changes from $.25$ to 2 in steps of $.25$, the area containing $\Delta Var < 0$ increases. With the increased area, there is space where ΔVar decreases with attention, but affects excitatory input most

Methods

These differential equations describe the change in firing rates for each population. f_θ calculates the mean firing rate of population θ given a fixed input, $\theta \in E, I$.

$$\tau_E \frac{dr_E}{dt} = -r_E + f_E\left(\mu_E + J_{EE} r_E - J_{EI} r_I + \sigma_E \xi(t)\right),$$
$$\tau_I \frac{dr_I}{dt} = -r_I + f_I\left(\mu_I + J_{IE} r_E - J_{II} r_I + \sigma_I \xi(t)\right).$$

V_E describes the population variance over long time periods. The slope of f_θ increases with attention and corresponds with L_θ. The equation for population variance is dependent on these changes.

$$V_E = \left| \frac{L_E(\frac{1}{\beta} J_{II} L_I(\sigma_E - \sigma_I) + \sigma_E)}{1 + \frac{1}{\beta} J_{II} L_I - \frac{1}{\alpha} J_{IE} L_E} \right|^2$$

To find where an attentional path could lie ($\Delta V_E < 0$), the line $\Delta V_E = 0$ was computed along the input space $(\Delta\mu_I, \Delta\mu_E)$.

To the right of this line, variance decreases along the attentional path.

To break the coupling symmetry, the variables α and β such that $\alpha, \beta \neq 1$ were introduced to the equation computing variance.

α and β were given values greater and less than 1. One of these variables was changed while the other was held at 1.

Discussion

Disrupting the coupling symmetry in the attentional modulation model shows that increases in both α and β result in cases in which $\Delta\mu_E > \Delta\mu_I$ where variance decreases.

In these cases, the excitatory population is affected more than the inhibitory population contrary to when symmetry is maintained.

Future Research

- Analyze cases in which variance decreases with attention and $\Delta\mu_E > \Delta\mu_I$. Consider internal inputs in the system along with external inputs
- Explore how coupling strengths affect eigenvalues, network stability, and other model outputs

References

[1] Cohen MR, Maunsell JH. *Attention improves performance primarily by reducing interneuronal correlations.*. Nature Neuroscience 12:1594-1600, 2011.

[2] Kanashiro T, Ocker GK, Cohen MR, Doiron B . *Attentional Modulation of Neuronal Variability in Circuit Models of Cortex.* eLife Journal, 2017.

Acknowledgements

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