Modeling attentional modulated spike count correlation in macaque V1

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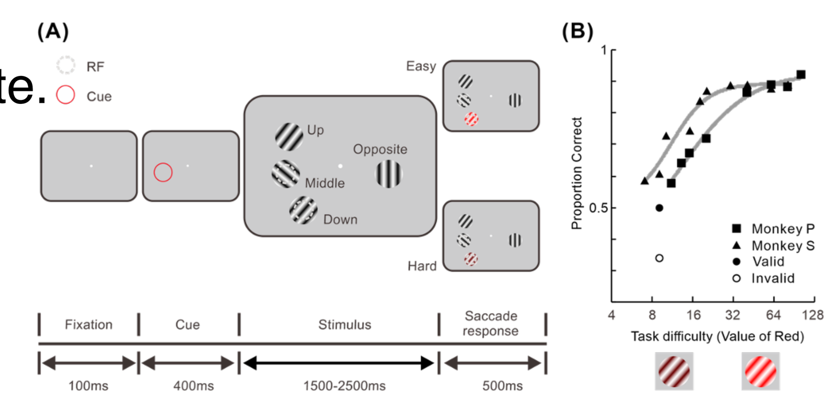
Introduction

- **Attention** is an essential cognitive function to facilitate information processing.
- Visual spatial attention **enhances** the activation of target neurons, and also **decreases** the spike count correlation among them.
- Recent experiments(1) found that attention can **either increase or decrease** firing rate.
- Attentional load can **non-monotonically** tune the spike count correlation between different types of neurons.
- This work aims to understand the mechanism for these nontrivial modulations.



Model

Neural Rate Model(2)

$$\tau\frac{d}{dt}\mathbf{R}(t) = -\mathbf{R}(t) + \mathscr{F}\left(\mathrm{W}\mathbf{R}(t) + \overrightarrow{\mu}^{\mathrm{ext}} + \mathbf{A}\Delta\overrightarrow{\mu} + \sigma\overrightarrow{\xi}(t)\right)$$

Population mean firing rate

$$\mathbf{R} = \left[r_{F_1}, r_{F_2}, r_{I_1}, r_{I_2}, r_{N_1}, r_{N_2}\right]^T$$

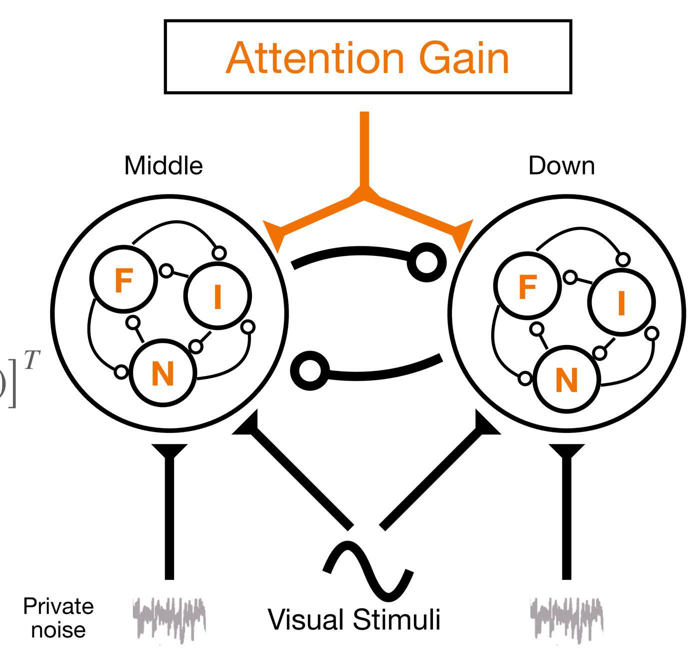
Activation function:

$$\mathscr{F}(\mathbf{x}) = \left[\mathscr{F}(x_1), \mathscr{F}(x_2), \cdots, \mathscr{F}(x_6)\right]^T$$

Attention Load: $A \in [0,1]$

Maximum attentional input strength: $\Delta\mu$

Attention gain matrix: $\mathbf{A} = \mathrm{diag}\,(1,1,1,1,0,0)$



Mean Field Theory(3) (MFT)

- Consider the steady state solution of the equation, i.e., $\frac{\mathrm{d}}{\mathrm{d}t}\mathbf{R}_m(t) = 0$

$$\mathbf{R}_m = \mathbf{L}\left(\mathrm{W}\mathbf{R}_m + \overrightarrow{\mu}^{\mathrm{ext}} + \mathbf{A}\Delta\overrightarrow{\mu}\right)$$

- Dynamics of fluctuations: $\mathrm{d}\delta\mathbf{R} = \mathbf{M}\delta\mathbf{R}\mathrm{d}t + \mathbf{D}\mathrm{d}\mathbf{W},$

where $\mathbf{M} = \frac{1}{\tau}\left(\mathbf{L}_m\mathbf{W} - \mathbf{I}\right), \quad \mathbf{D} = \frac{\sigma}{\tau}\mathbf{L}_m, \quad \mathrm{d}\mathbf{W} = \mathrm{dt}\left[\overrightarrow{\xi}_1(t), \cdots, \overrightarrow{\xi}_n(t)\right]^T.$

- Ito formula: $\mathrm{d}\left\langle\delta\mathbf{R}\delta\mathbf{R}^T\right\rangle = \left\langle\delta\mathbf{R}\delta\mathbf{R}^T\right\rangle\mathbf{M}^T\mathrm{d}t + \mathbf{M}\left\langle\delta\mathbf{R}\delta\mathbf{R}^T\right\rangle\mathrm{d}t + \mathbf{D}\mathbf{D}^T\mathrm{d}t$
- Solve Lyapunov equation:

$$\mathbf{C}\mathbf{M}^T + \mathbf{M}\mathbf{C} + \mathbf{D}\mathbf{D}^T = 0$$

Conclusions

- Our model showed that **inhibitory projections** play vital roles in modulation.
- Our m*ean field analysis* tells the range of parameter that acquired for the monotones of spike count correlation modulation.
- Our model can flexibly predict the modulation of spike count correlation under different types of input drives as well as input contrasts.
- Our model can provide the intuition towards the potential candidate for those different types of attention modulated neuron types.
- Based on these, we can further build **spike neuronal network** models to verify our hypothesis towards the top-down attentional mechanism.

Results

- Simulate rate model driven by constant input with Gaussian white noise. Apply MFT analysis to scan the feasible parameter subspace for W.

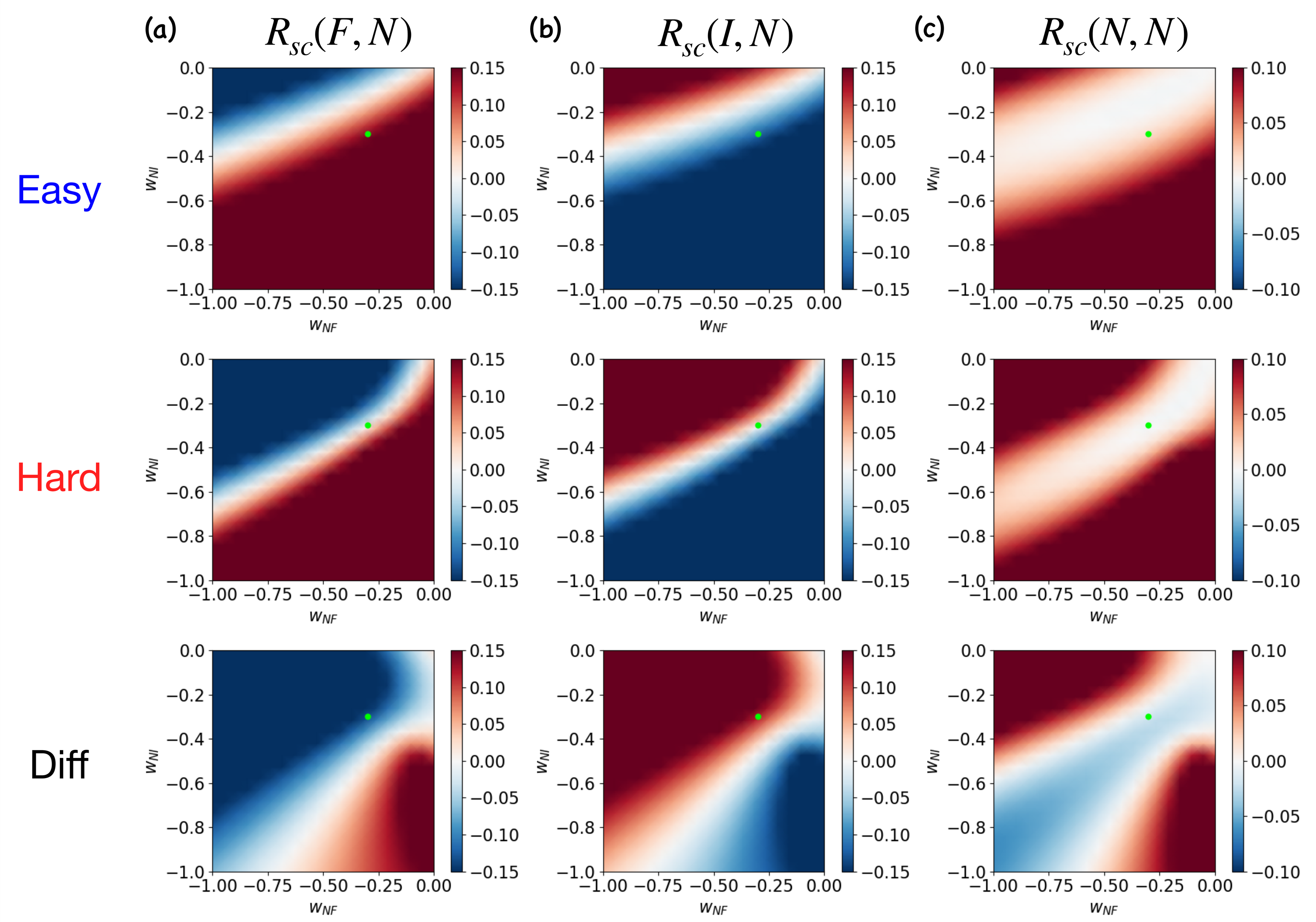


Fig 1. MFT Analysis. (a) The colormap of R_{sc} between F and N neurons for w_{NF} and w_{NI}. Top panel for easy tasks, middle panel for hard tasks, and bottom panel for the difference of R_{sc} between easy and hard tasks. (b)-(c) The colormap of R_{sc} between I-N pairs in (b) and those between N-N pairs in (c). Settings of subfigures are similar to those in (a). Other parameters are also scanned (not shown).

- Simulate rate model driven by *sine-wave* input current (modeling Gabor stimuli in experiments) with private Gaussian noise. The same connectivity matrix W was used as the constant drive case.

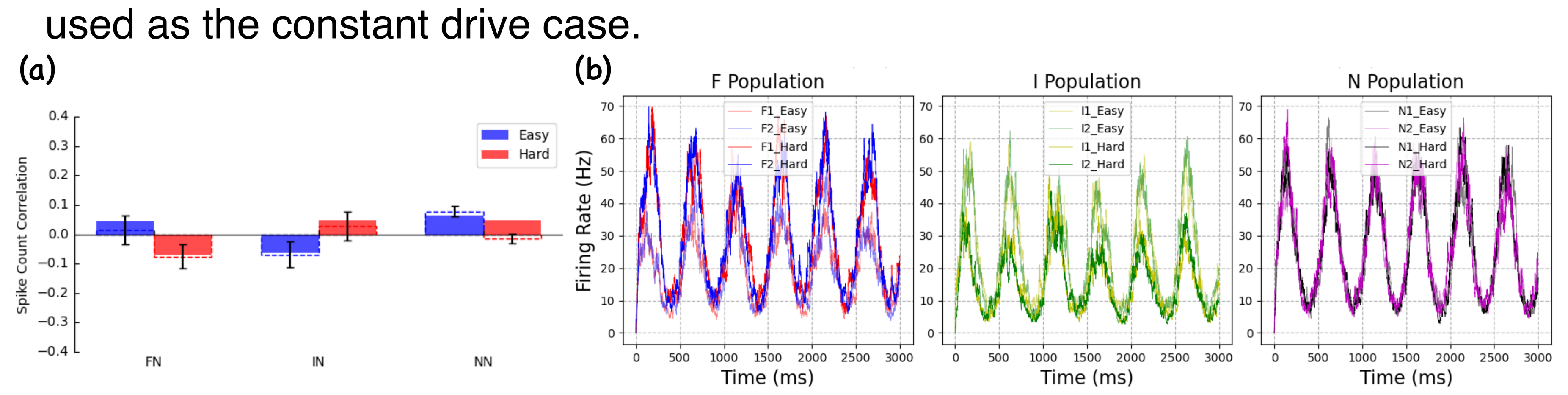


Fig 2. Model simulations. (a). The spike count correlation (R_{sc}) of three types of neuron pairs for easy and hard tasks. The dashed bars and error bars are the mean and standard deviation of mean of R_{sc} measured in experiments. The solid bars are from model simulations. (b). The firing rate of three types of attention modulated neurons. Transparent curves are for easy task, and solid curves are for the hard task.

- Predictions about R_{sc} modulation for other difficulty and input strength (contrast).

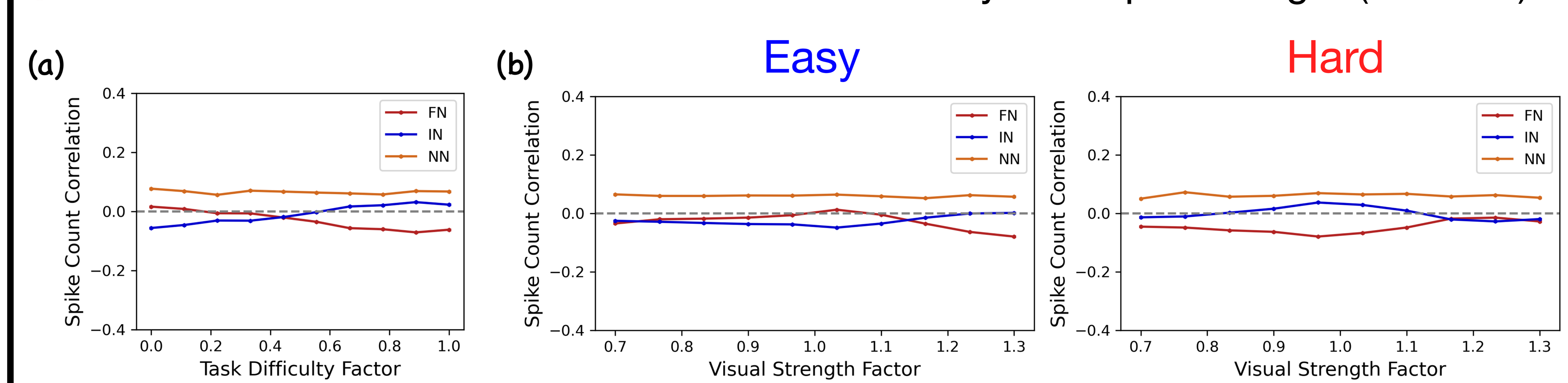


Fig 3. Model predictions. (a) The value of R_{sc}s between three pairs for different task difficulties. (b) The value of R_{sc}s for different input strength (or input contrast).

Reference

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(2) Kanashiro, T., Ocker, G. K., Cohen, M. R., & Doiron, B. (2017). Attentional modulation of neuronal variability in circuit models of cortex. *ELife*, *6*, 1–37.

(3) Gardiner CW. Handbook of Stochastic Methods for Physics, Chemistry and the Natural Sciences. 3rd ed. Springer-Verlag; 2004.