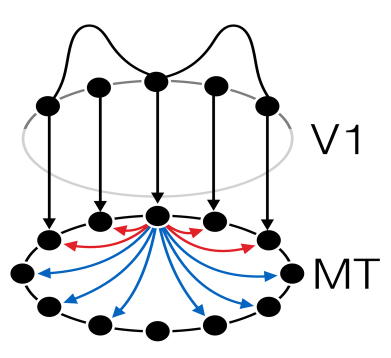

Understanding the impact of recurrent interactions on population tuning

Application to MT cells characterization

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Context & Summary

A lot of theoretical work has been done in understanding neural computation and dynamics regulated by excitatory and inhibitory interactions [5, 4] **but:**

- Most studies are conducted without structured input.
- Their impact in terms of sensory information processing is often missing.

The goal of this work is to bridge this gap by focusing on the impact of lateral interactions on population tuning.

▶ Methodology

- A ring network model under neural fields formalism with a structured input.
- Bifurcation analysis to understand model's behavior depending on connectivity and input parameters.

▶ Application to MT cells characterization

Neurons in the middle temporal (MT) visual area have been linked to 2D motion perception [3, 1]. Direction-selective cells encode either (local) component or (global) pattern motion. However, these properties depend on the spatiotemporal inputs (e.g. plaids vs. Random Dot Patterns (RDPs)) as well as on the recurrent local interactions. We aim to better understand how the local interactions in conjunction with driving stimuli lead to different tuning behaviors.

Model description

▶ Ring model with Excitatory/Inhibitory interactions

$u(\theta,t)$ ($\theta \in [-\pi,\pi)$) denotes a population of directionally tuned MT neurons with dynamics governed by:

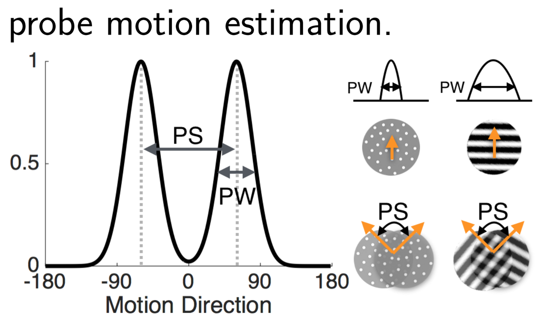
$$\frac{du(\theta,t)}{dt} = -u(\theta,t) + \int_{-\pi}^{\pi} J(\theta-\phi)S(\mu u(\phi,t))d\phi + I_{ext}(\theta),$$

where, J is the connectivity kernel, S is a sigmoid function (μ regulates the sigmoidal gain), I_{ext} is the driving input.

▶ Definition of I_{ext}

I_{ext} is defined as a linear combination of gaussian bumps. It allows us to represent different kinds of stimuli used to probe motion estimation.

- Peak width (PW) : Representative of uncertainity in local velocity estimates (standard dev. of the bump)
- Peak separation (PS) : Directional difference between component motions.



▶ Definition of $J_{g_e,\sigma_e,g_i,\sigma_i}(\theta)$

Let $J_{g_e,\sigma_e,g_i,\sigma_i}(\theta)$ denote weighted difference of gaussians:

$$J_{g_e,\sigma_e,g_i,\sigma_i}(\theta) = g_e G(\theta,\sigma_e) - g_i G(\theta,\sigma_i),$$

where, $G(\theta,\sigma)$: Gaussian function, g_e: excitatory strength, σ_e: extent of excitatory surround, g_i: inhibitory strength, σ_i: extent of inhibitory surround.

Numerical study of the model

▶ Exploration of the connectivity space with $\tilde{J}_{\alpha,\beta}$

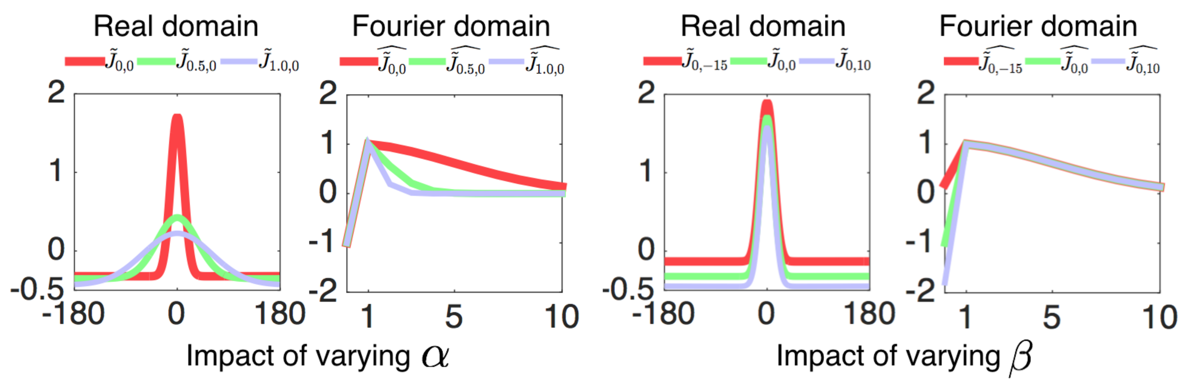
$$\tilde{J}_{\alpha,\beta}(\theta) = J_{g_{e_\alpha},\sigma_{e_\alpha},g_{i_\alpha}+\beta,\sigma_i}(\theta)$$

- Assumption: We consider the case of a uniform lateral inhibition, so σ_i is fixed to a large value ($\sigma_i = 10\pi$).
- α is a parameter to smoothly vary the extent of excitatory surround from narrow to broad while mainting constraints imposed on specific Fourier components.
- β is a free parameter to regulate the strength of lateral inhibition.

Numerical study of the model (Cont.)

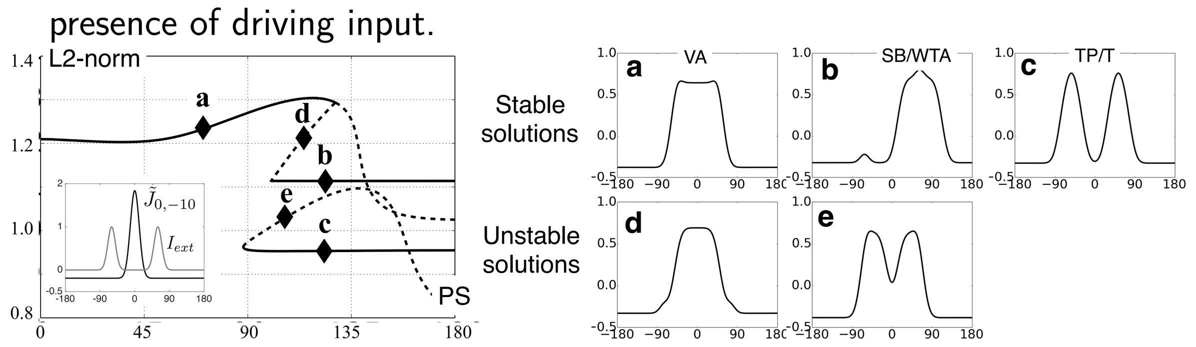
▶ Connectivity kernels: $J_{\alpha,\beta}$

- On the left, connectivity kernels with narrow to broad excitatory extent.
- On the right, connectivity kernels with low to high lateral inhibition strength.



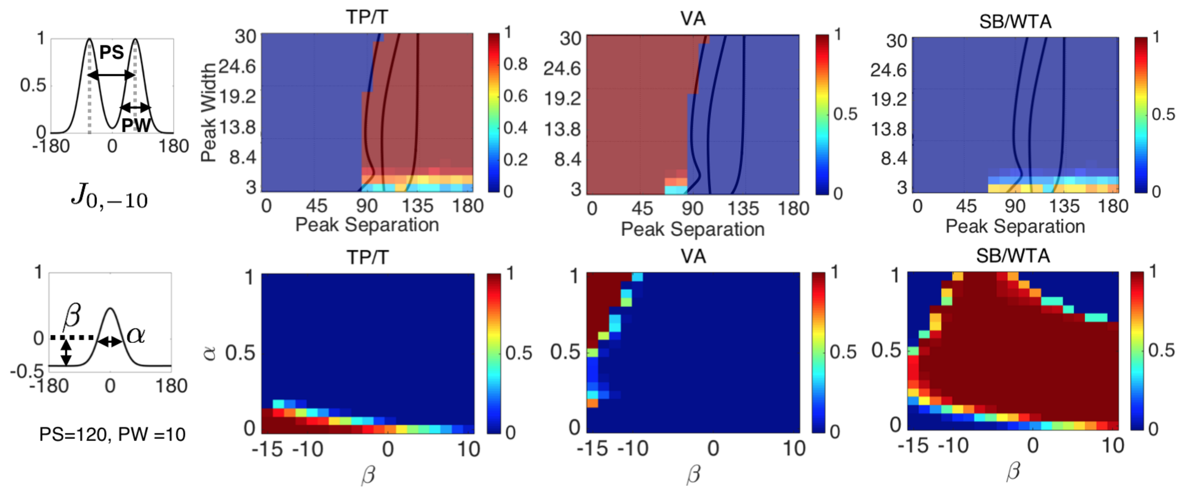
▶ Solution space

- Stable and unstable solutions the network could converge to under the presence of driving input.



▶ Likelihood of convergence

We estimate the strength of the stable solutions using random noise as initial condition w.r.t. input and kernel parameters (100 trials)



- There are parameter regimes where multiple solutions co-exist.
- The stability of the solution also changes quite sharply w.r.t to parameters of the driving input.
- All theoretically stable solutions are not reached unless there is a bias in the initial conditions.

Conclusion

Our model demonstrates that recurrent interactions can shape direction tuning of MT neurons. The properties of both excitation width and inhibition strength explain the different tuning classes and their dynamics with respect to spatiotemporal properties of the input. Moreover, prototypical tuning shapes (e.g. VA, SB and TP) correspond to different regimes of a single dynamical system, where sharp transitions can be identified.

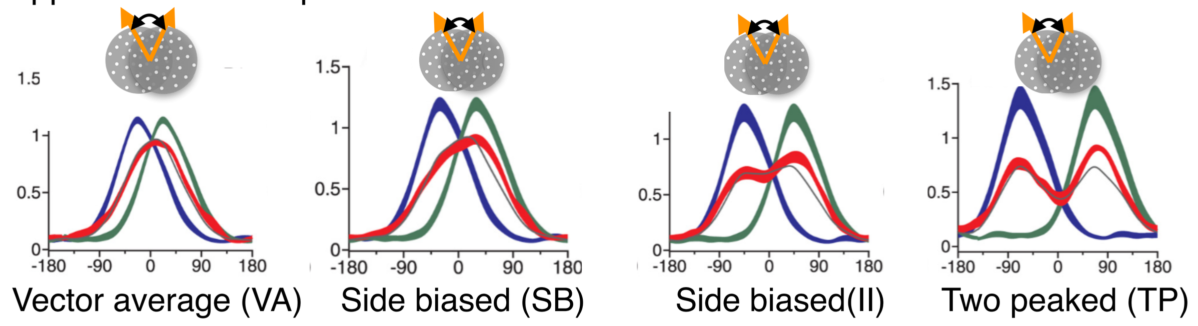
References

[1] R.T. Born and D.C. Bradley. *Annu. Rev. Neurosci*, 28, 2005.
[2] J. Scott McDonald, Colin W. G. Clifford, et al. *Journal of Neurophysiology*, 111(2), 2014.
[3] J.A. Movshon, E.H. Adelson, et al. *Pattern recognition mechanisms*, 1985.
[4] M. E. J. Raijmakers, Han L. H. van der Maas, et al. *Biological Cybernetics*, 75(6), 1996.
[5] H.R. Wilson and J.D. Cowan. *Biophys. J.*, 12, 1972.
[6] Jianbo Xiao and Xin Huang. *The Journal of Neuroscience*, 35(49), December 2015.

Understanding tuning behavior of MT cells

▶ Experimental Observation

MT cells show different tuning behaviors [6] when stimulated with two overlapped motion components such as RDPs or Plaids.

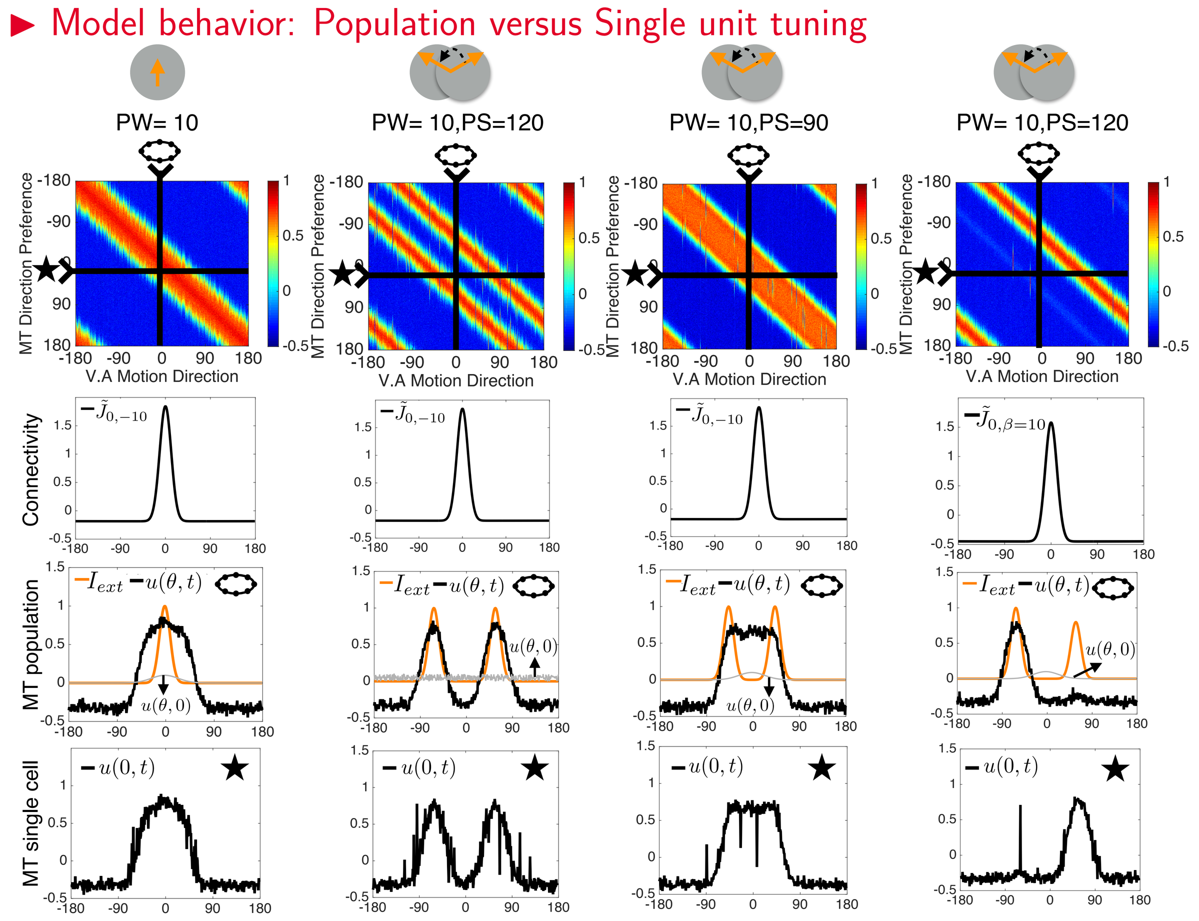


▶ Question 1

- Could recurrent local interactions in the feature space (direction of motion) lead to these observed tuning behaviors?

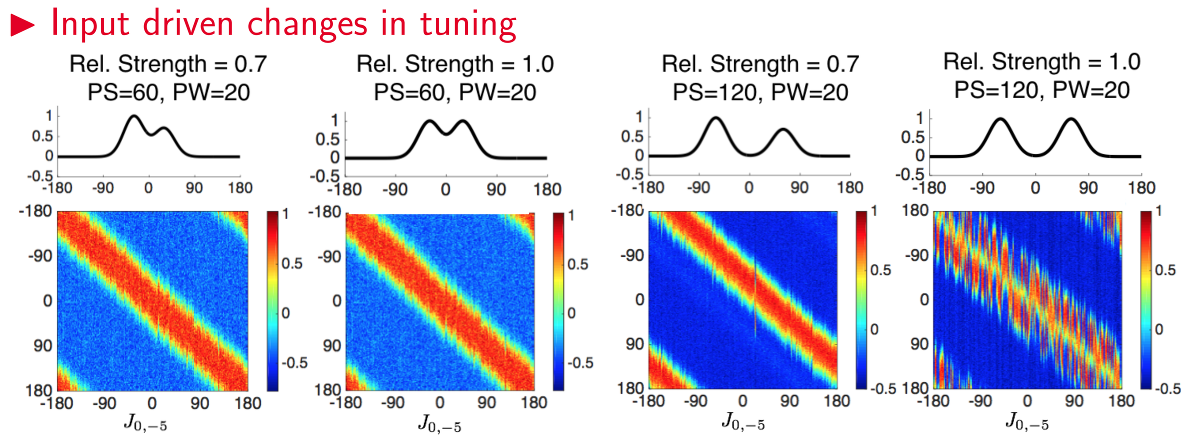
In terms of modelling, can a single model reproduce these behaviours by considering local recurrent interactions in the feature space?

▶ Model behavior: Population versus Single unit tuning



- *Observation*: Recurrently interacting homogeneous population of Direction Selective (DS) cells can reproduce different kinds of tuning observed experimentally.
- Fluctuations can occur at single cell level due to the multistability.

▶ Input driven changes in tuning

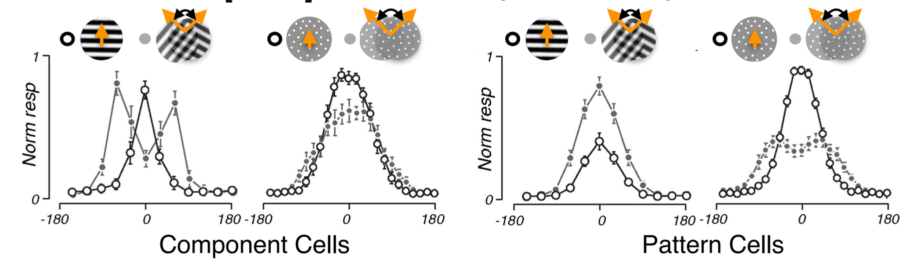


- Model behavior changes from VA to SB or consistent SB to fluctuating component selection. These behavior changes are driven by changes in component separation and relative strength.
- Assymetries in the input could significantly stabilize MT single unit tuning from a fluctuating WTA to SB.

Predicting tuning behavior

▶ Experimental Observation

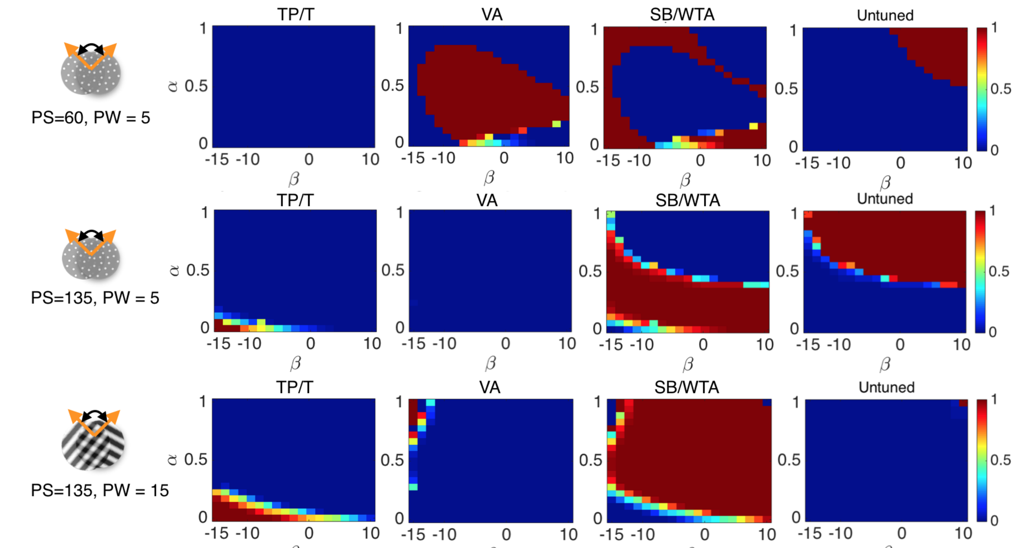
Pattern vs. component tuning classification has been traditionally obtained with plaid patterns [3] but several empirical studies have shown that such classfication cannot translate from one stimulus class to another [2, 6], for example from plaid stimuli to RDPs.

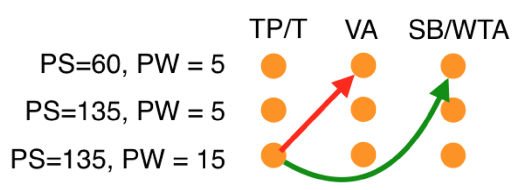


▶ Question 2

Can our model capture the changes in the tuning behavior with respect to changes in the input and therefore explain the difficulty in predicting the tuning behavior across stimuli type?

▶ Model behavior: Connectivities w.r.t to Input stimuli



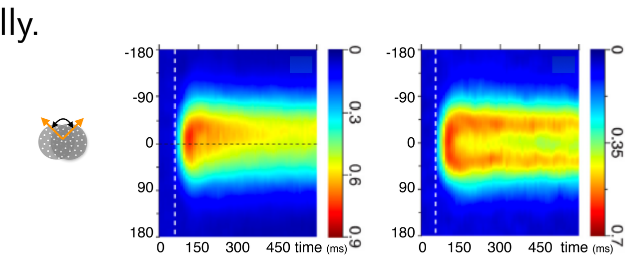


- Extent of overlap between likelihood of different tunings vary across stimuli and certain transitions have a very weak likelihood.

Temporal dynamics

▶ Experimental Observation

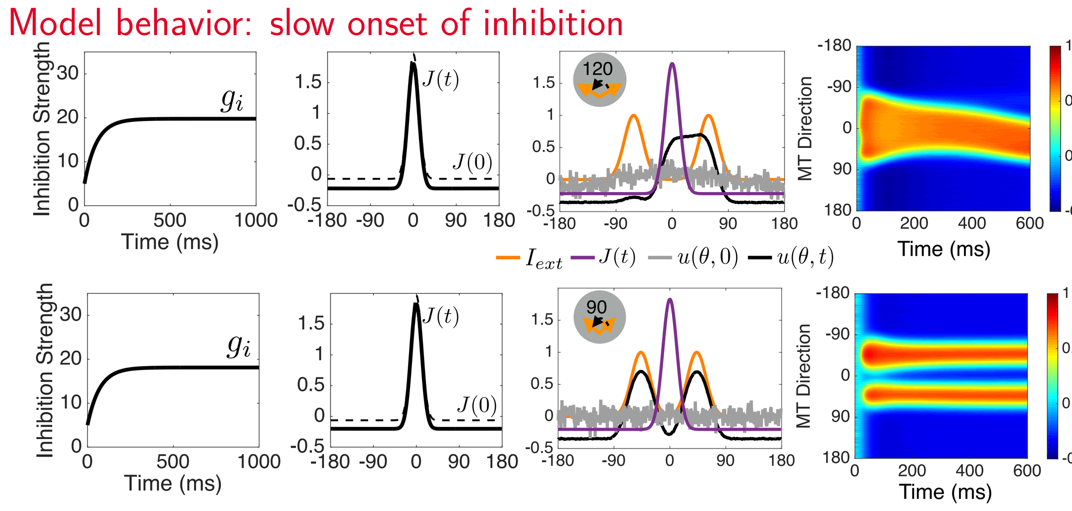
Temporal dynamics of MT cells show tuning transitions [6] and develop their selectivity gradually.



▶ Question 3

Can this be explained by temporal dynamics of inhibition?

▶ Model behavior: slow onset of inhibition



- Slow onset of inhibition could lead to a lack of tuning behavior in the initial time period, lateral competition then leads to observed tuning behaviors.

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