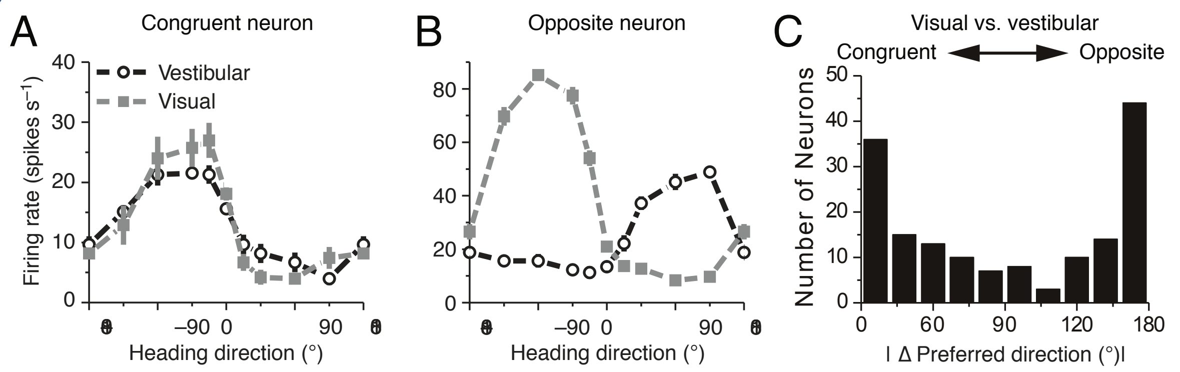
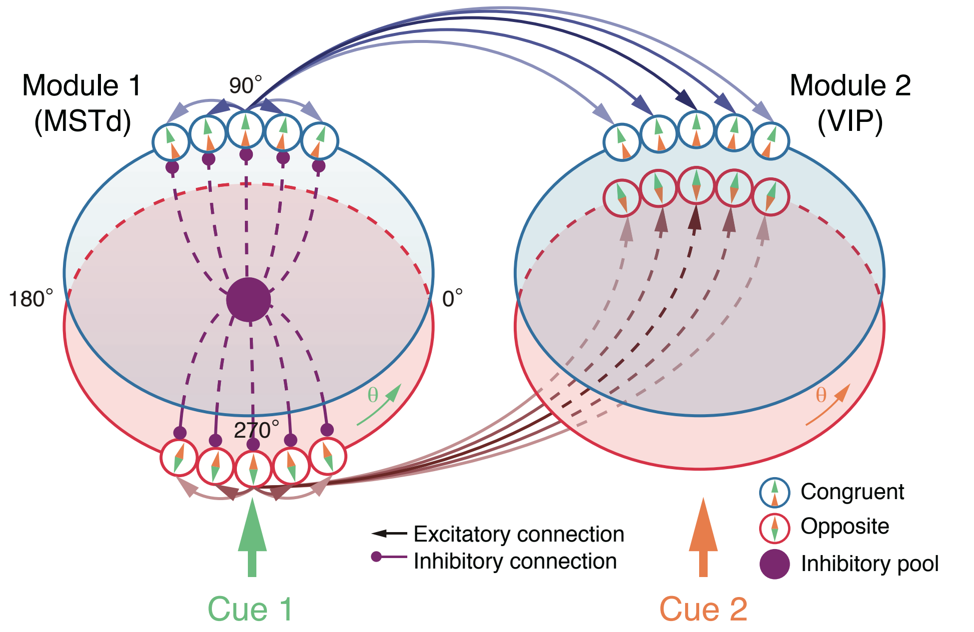
香港科技大學
THE HONG KONG UNIVERSITY OF SCIENCE AND TECHNOLOGY

Bayesian Model for Multisensory Integration and Segregation

Xiangyu Ma, He Wang, Min Yan, Wen-Hao Zhang and K. Y. Michael Wong



Congruent and opposite neurons in MSTD and VIP. Tuning curves of a congruent neurons (A) and an opposite neuron (B) respectively, and the histogram of two different types of neurons (C).



In a recently proposed decentralized neural network model (Zhang et al. 2019), each module consists of two groups of neurons, congruent (blue circles) and opposite (red circle) neurons. Congruent neurons implement integration, while opposite neurons compute cue disparity information for segregation.

Weaknesses

(1) The peak position of the firing rate profile deviates from the Bayesian result.

(2) The model was based on the prior that cues 1 and 2 are always correlated.

Projection Methods

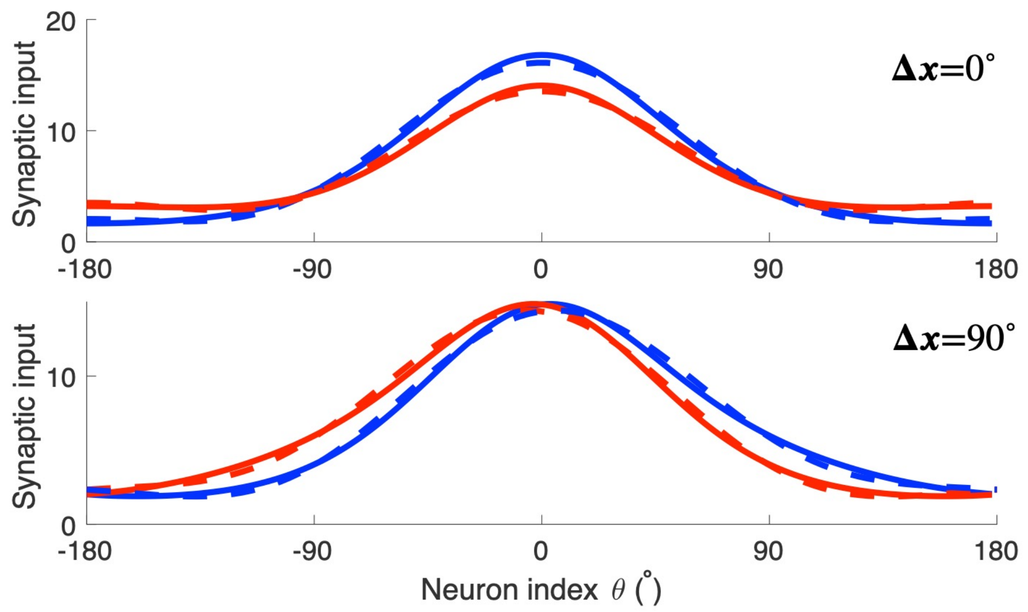
(1) We approximate the solution to the dynamical equations to be

$$\psi_m = u_{m0} + u_{m1}\cos(y_1 - s_1) + u_{m2}\cos 2(y_1 - s_1) + u_{m3}\sin 2(y_1 - s_1), \qquad m = 1,2.$$

The background, height, position, width and skewness are largely determined by the coefficients u_{m0}, u_{m1}, s_m, u_{m2} and u_{m3} respectively.

(2) Multiplying both sides of dynamic equations of congruent and opposite groups by 1, $\cos(y - s_m)$, $\sin(y - s_m)$, $\cos 2(y - s_m)$ and $\sin 2(y - s_m)$ in turn and integrating over y, we obtain the steady state equations for this set of coefficients after averaging over noise.

(3) By considering the linear perturbation around the steady state, the variance $\hat{\sigma}_m^2$ of the peak positions $\hat{s}_m$ can be found.



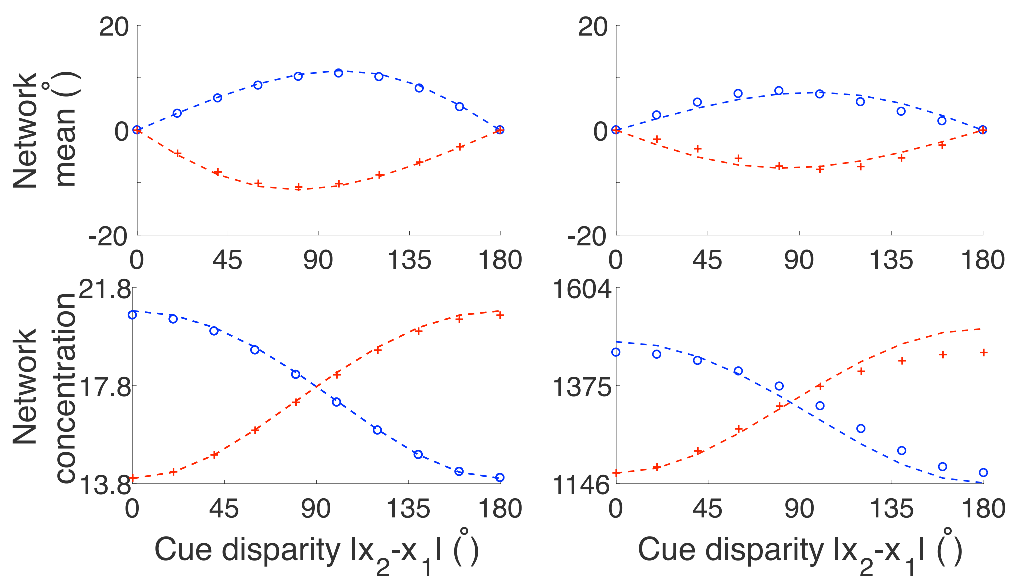
Bump profiles (synaptic inputs) of congruent and opposite groups in module 1 without noise. The blue and red colors represent congruent and opposite groups respectively. Solid lines: simulation results, dashed lines: analytic results by using projection method.

Output-Dependent Noise

In order to implement Bayesian prediction, we define the length of the output population vector

$$\hat{A} \equiv \bmod\left(\frac{1}{N}\sum_{y=-\pi}^{\pi} R_m(y)e^{jy}\right) = \frac{u_1}{2D}\sqrt{(2u_0 + u_2)^2 + u_3^2},$$

where j is the imaginary unit. We introduce the output-dependent noise term: $\sqrt{F_0\hat{A}}\epsilon_m$, where ϵ_m is Gaussian white noise of zero mean and variance satisfying $\langle \epsilon_m(y,t), \epsilon'_m(y',t')\rangle = \delta'_{mm}\delta(y - y')\delta(t - t')$.



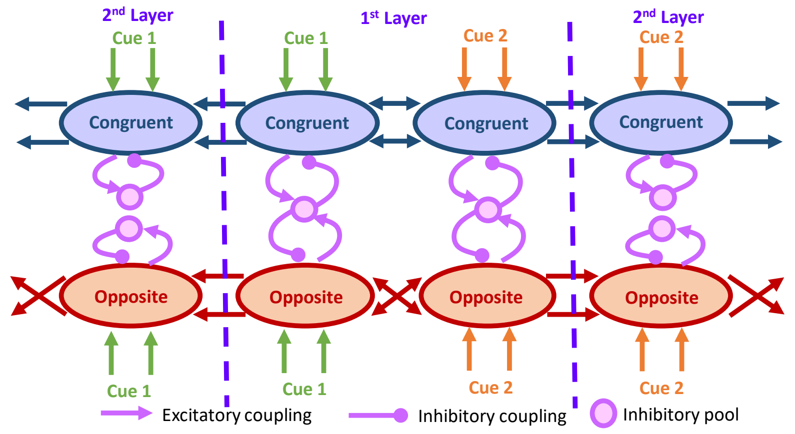
Output-dependence noise improves the agreement between the model and Bayesian prediction when the input is weak ($I_1 = I_2 = 0.01\,U_0$, left column) and not so good for strong input ($I_1 = I_2 = 0.7\,U_0$, right column). Symbols: network results; dashed lines: Bayesian prediction. The blue and red colors represent congruent and opposite groups in module 1 respectively. $x_1 = 0$.

Priors with an Independent Component

We consider the following two-component prior,

$$p(s_1, s_2) = \frac{p_0}{2\pi}V(s_1 - s_2, \kappa_s) + \frac{1 - p_0}{(2\pi)^2}.$$

To deal with this prior, we propose a network architecture with a second layer of neurons.



Network architecture for priors with correlated and independent components. Parallel arrows represent congruently connected couplings. Crossed arrows represent couplings shifted by π.

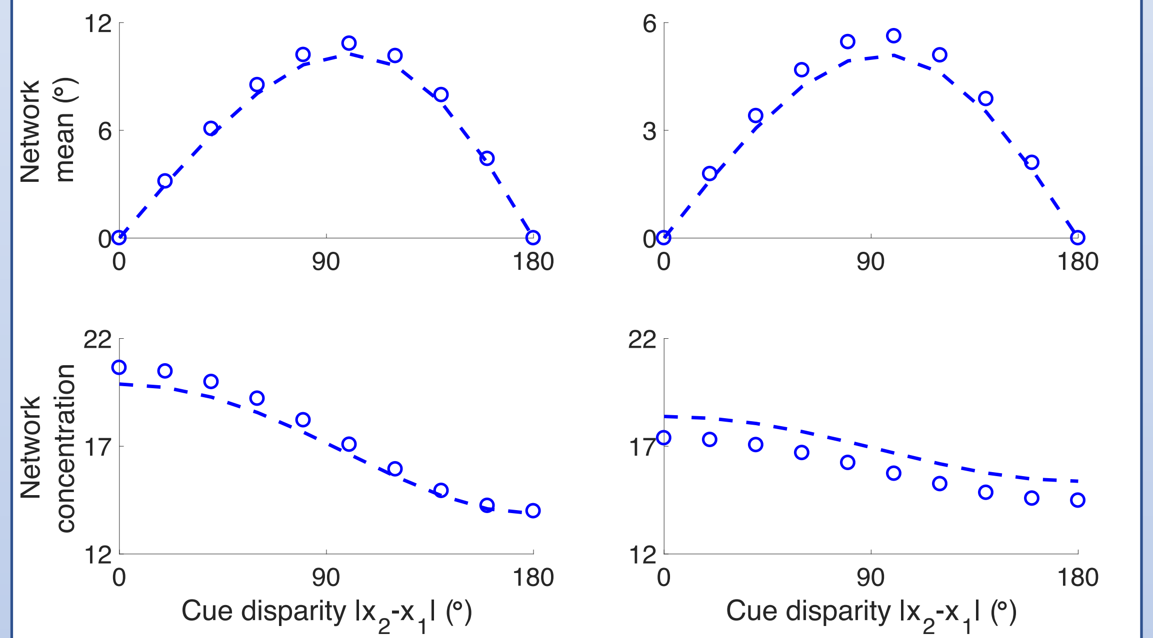
Network encoding

Assuming that $p(x_m)$ and $p(s_m)$ are uniform distributions, we take the derivative of $p(s_1, s_2|x_1, x_2)$ with respect to s_1 to be zero

$$\kappa_s^B \sin(s_2 - s_1) + \kappa_1^B \sin(x_1 - s_1) = 0.$$

where κ_s^B and κ_1^B denote the concentrations given by the probabilistic model. Meanwhile, the dynamic equation projected onto the position mode is given by

$$HJ_{rp}\sin(s_2 - s_1) + \frac{F}{u_1}\sin(x_1 - s_1) = 0.$$



Outputs of the congruent groups from the first (left column) and the second layer (right column). Symbols: network results; dashed lines: Bayesian network. Note that we take the average of c_0 among 10 trials (symbols). Besides, we have $\langle u_1\rangle$ and $\langle H\rangle$ in the same way. This result is in weak input limit ($I_1 = I_2 = 0.01U_0$), and we set $p_0 = 0.5$ for the right column (second layer).

Conclusion

(1) Output-dependent noise improves the agreement of integrated posteriors and disparity information with Bayesian prediction, especially in the weak input limit.

(2) For composite priors, additional modules can be used to produce Bayesian prediction of the integrated information.

(3) The Bayesian model has a close relationship with the network structure. This holds true even for the second layer in the proper ranges for parameters.