Learning opposite neurons in a firing rate-based model

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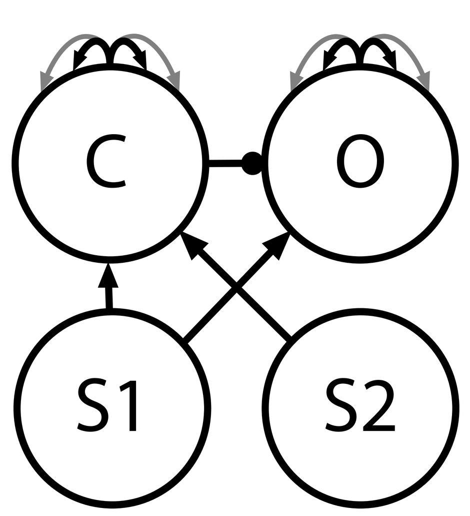
Introduction

- Opposite neurons are found in brain areas (MSTd and VIP) responsible for integration of visual and vestibular self-motion cues.
- Opposite neurons combine *opposite information*, for example a rightward vestibular motion cue and a leftward visual motion cue.
- This is in contrast to *congruent neurons*, also found in the same areas, that combine congruent information and perform multisensory integration.
- While congruent neurons can be learned easily with Hebbian learning, the same cannot be said for opposite neurons. We show that our model can learn these opposite neurons.

Methodology

Model architecture and dynamics



Excitatory connections:
Inhibitory connections:

Our model consists of:
- two sensory inputs S1 and S2
- congruent neurons C
- opposite neurons O

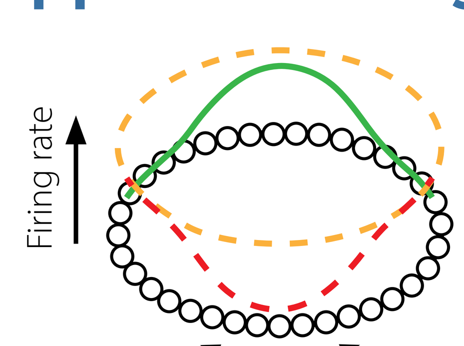
Neurons lie on a 1D ring indexed by angle θ

- There are recurrent excitation and divisive normalization among C and O neurons
- Recurrent connections are fixed, but feedforward connections (both excitatory and inhibitory) have the following learning rule

$$\tau\frac{dw_{ij}}{dt} = r_i(r_j - \alpha w_{ij})$$

where w_{ij} is the weight of a connection from neuron j to i, and r_i is the firing rate of neuron i.

Mechanism of opposite tuning

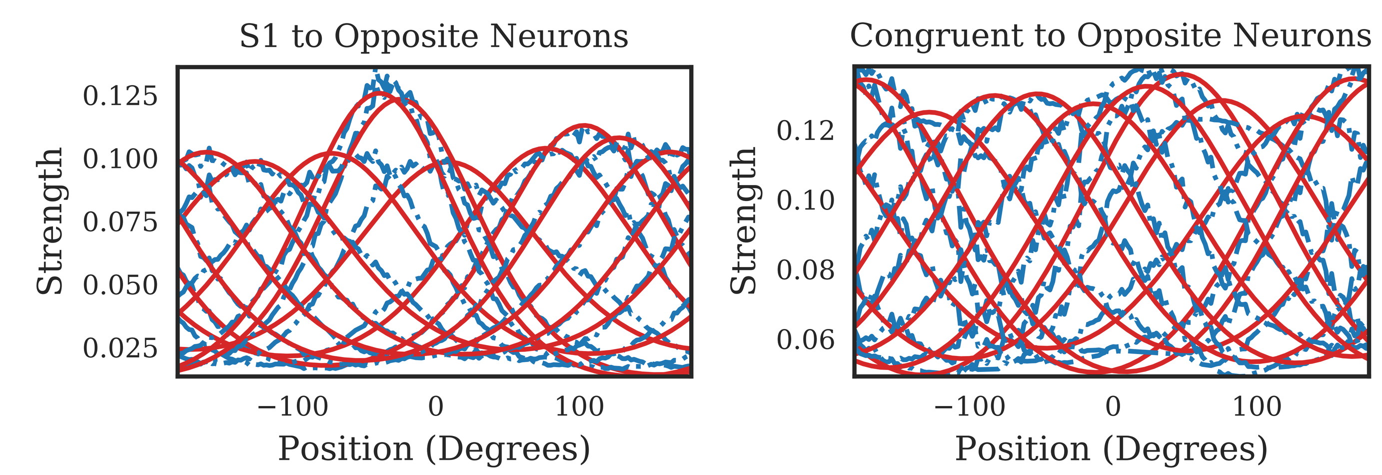


Opposite neurons
(indexed by θ, angle of tuning to S1)

- Orange line: Spontaneous activity of the ring of opposite neurons.
- Red line: S2 input at angle θ inhibits opposite neurons at θ.
- Green line: Recurrent excitation and divisive normalizations results in a bump of activity at $\theta + 180°$. Thus tuning to S1 and S2 is opposite.

Results

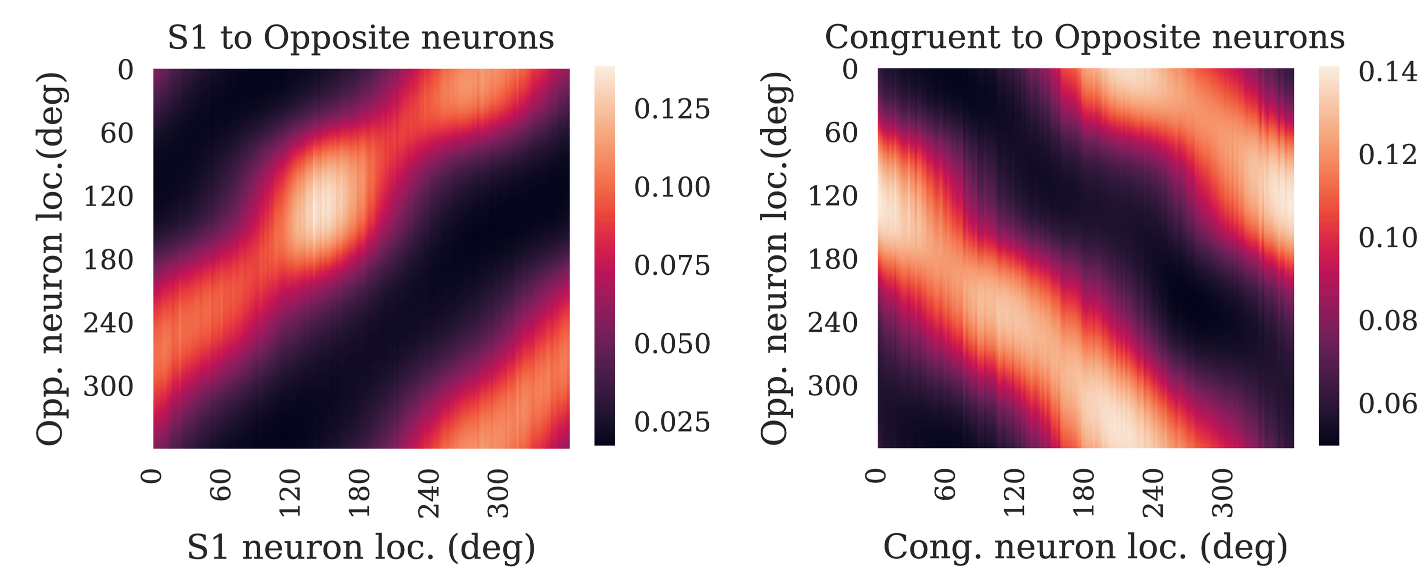
Learned feedforward weights are approximately von-Mises



Feedforward weights of 10 evenly-spaced opposite neurons. Blue lines are their feedforward weights, which are fitted with von-Mises distribution plotted in red.
Left: excitatory connections from S1 to O. Right: inhibitory connections from C to O.

Von-Mises distribution is a good fit for the shape of feedforward weights.

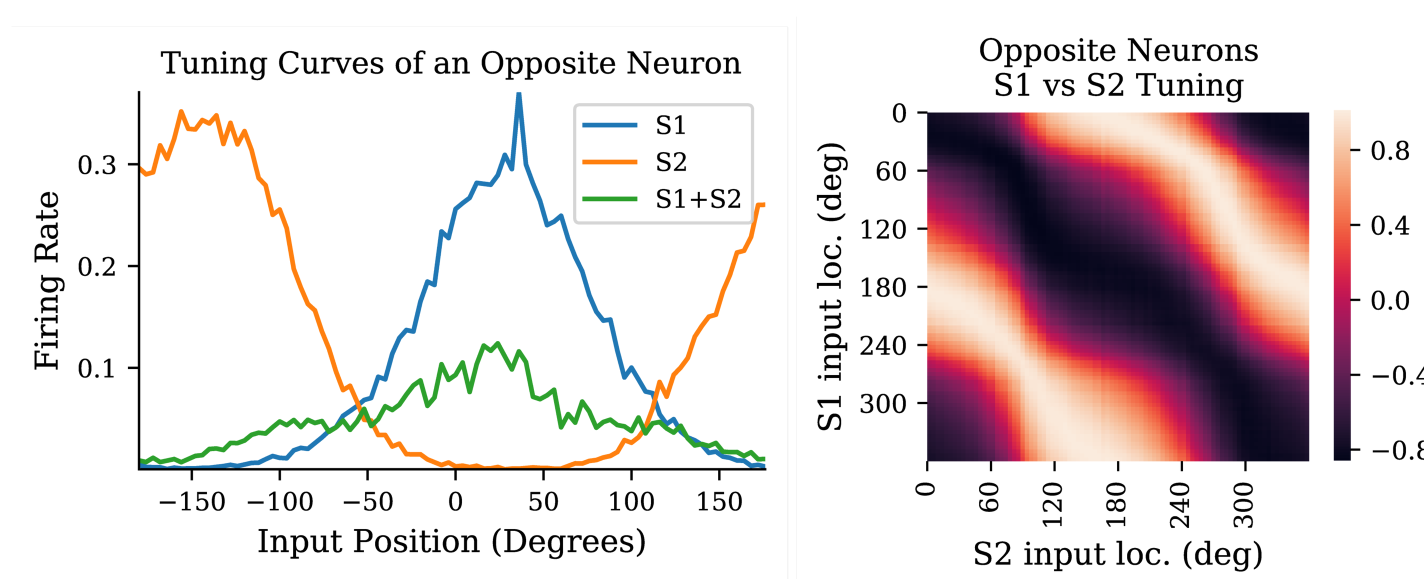
Opposite neurons are topographically organized



Weights matrices of feedforward connections to opposite neurons.
Left: excitatory connections from S1 to O. Right: inhibitory connections from C to O.

The bright ridges with slopes +1/-1 show that the opposite neurons are topographically organized in a clockwise or counter-clockwise manner.

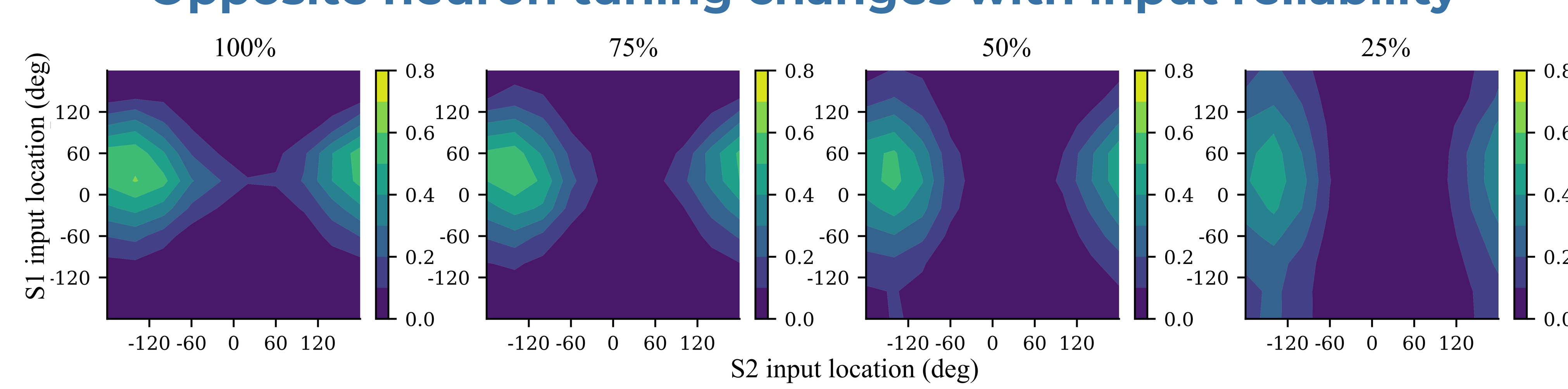
Opposite neurons learn correct opposite tuning



Left: An opposite neuron's tuning curves in response to S1 only, S2 only, and S1 + S2 inputs.
Right: Correlation of opposite neuron responses to S1 vs S2 input.

Left figure shows that the opposite neuron's tuning to S1 and S2 are opposite. Right figure shows that responses to S1 and S2 are most correlated when S1 and S2 are 180° apart.

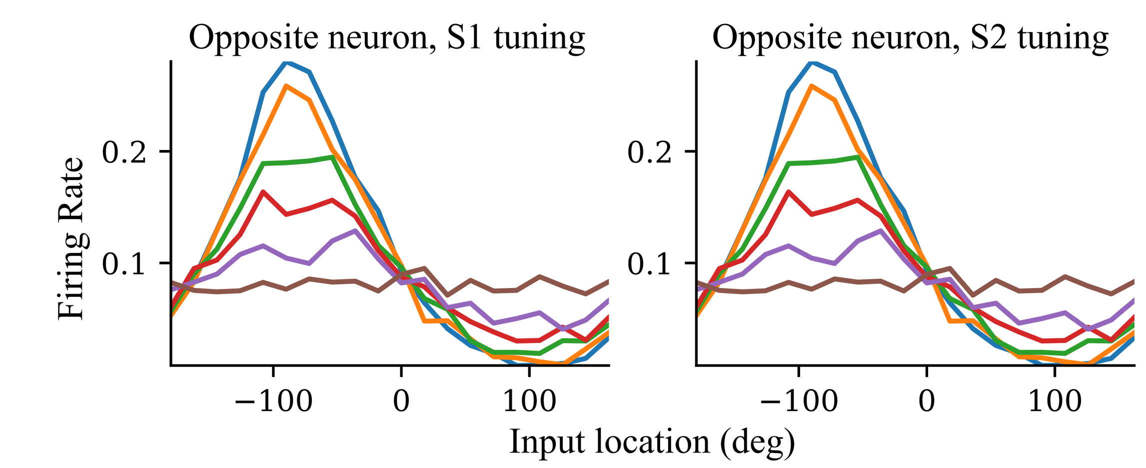
Opposite neuron tuning changes with input reliability



Tuning of an opposite neuron to S1 and S2 at the same time. Percentages indicate reliability of the S1 inputs used, where a decrease in reliability leads to a wider S1 input.

At 100% reliability, the opposite neuron prefers S1 input over S2 slightly. As reliability decreases, the opposite neuron becomes increasingly tuned to S2, agreeing with experimental results.

Opposite neuron tuning is "contrast-invariant"



Change in tuning of an opposite neuron as reliability of S1/S2 input decreases.
Color labelling of input reliability: blue - 100%, orange - 80%, green - 60%, red - 40%, purple - 20%, brown - 0%. *Left:* tuning to S1. *Right:* tuning to S2.

For both S1 and S2, decrease in input reliability decreases peak-to-peak amplitude of tuning response, but tuning width is invariant to input reliability, agreeing with experimental observations.

Discussion

Summary

- Using biologically realistic learning rules, our firing rate-based model can successfully learn opposite neurons with von Mises-shaped feedforward weights and preserves topographical organization of input.
- Our opposite neurons learn the correct opposite tuning. Change in tuning in response to change in input reliability agrees with experimental observations.

Future directions

- Information segregation with opposite neurons: Opposite neurons are hypothesized to be involved in segregating multisensory information in MSTd. Both theoretical analysis and computational modelling are needed to examine this hypothesis.
- Derivation of learning rules: While the Hebbian learning rule used is widely accepted, it is instructive to derive the rule we used from some objection function in order to understand the computational role of opposite neurons.

Acknowledgements

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