

Modeling perceptual learning of visual motion

Émilien Tlapale*, Barbara Anne Doshier*, Zhong-Lin Lu†

* Memory Attention Perception Laboratory, Department of Cognitive Science, University of California, Irvine, CA 92697

† Laboratory of Brain Processes, Department of Psychology, The Ohio State University, Columbus, OH 43210

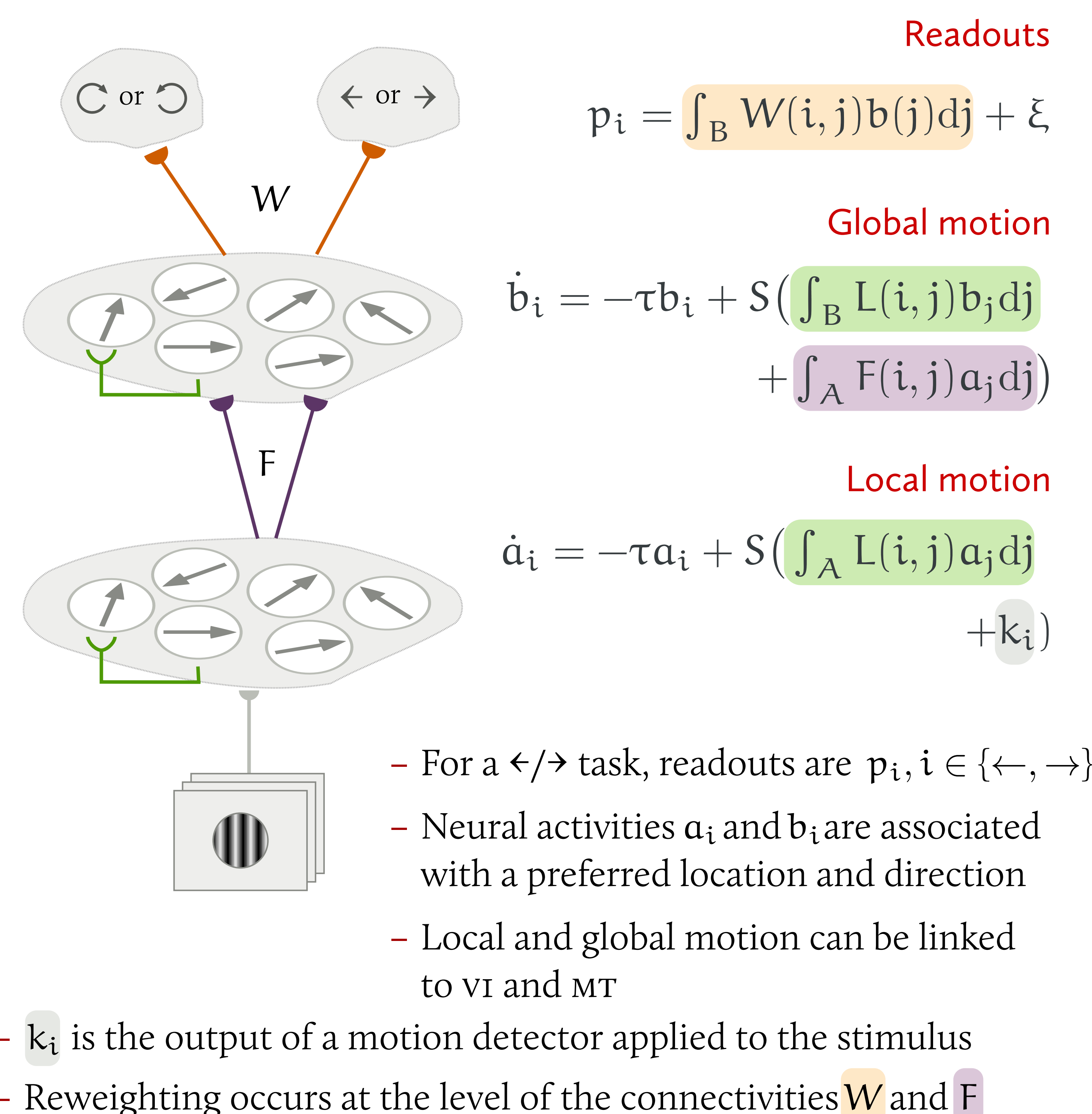
Objective

Repeated exposure or training on moving stimuli leads to improved performance in tasks such as motion detection or discrimination. Although numerous studies have reported perceptual learning in visual motion, identifying the underlying mechanisms and their cortical loci remains a major issue.

For spatial tasks such as orientation, perceptual learning has been modeled with readout reweighting of information from early sensory representations (Doshier & Lu, 1998, 1999; Petrov, Doshier & Lu, 2005). We develop and test a dynamical model of motion perception with connectivity reweighting to account for classic effects of learning in motion perception, and show results on a novel experiment.

Model architecture

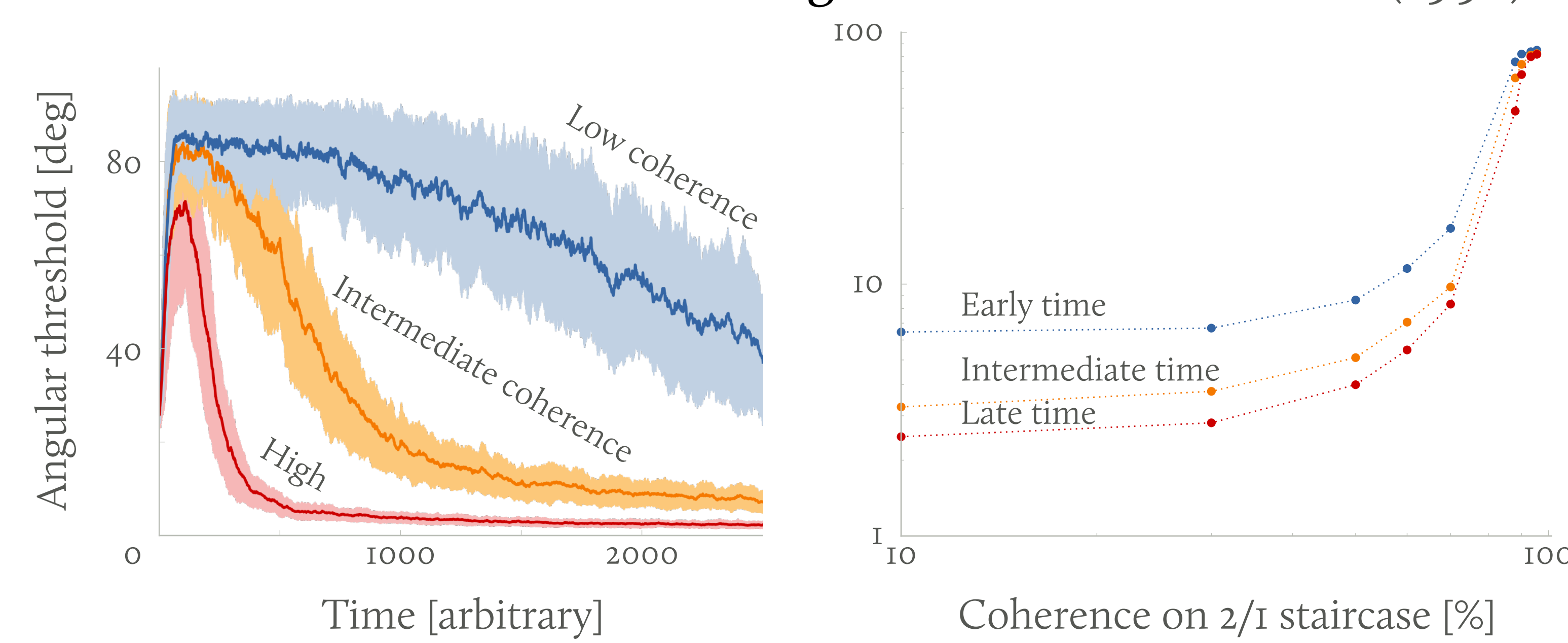
We model perceptual learning by incorporating connectivity reweighting into a large-scale dynamical model based on Tlapale et al (2010). This hierarchical model includes several cortical layers processing motion (V1, MT and readouts), their feedforward, feedback and lateral connections, and has been shown to elicit relevant percepts for a wide variety of motion stimuli



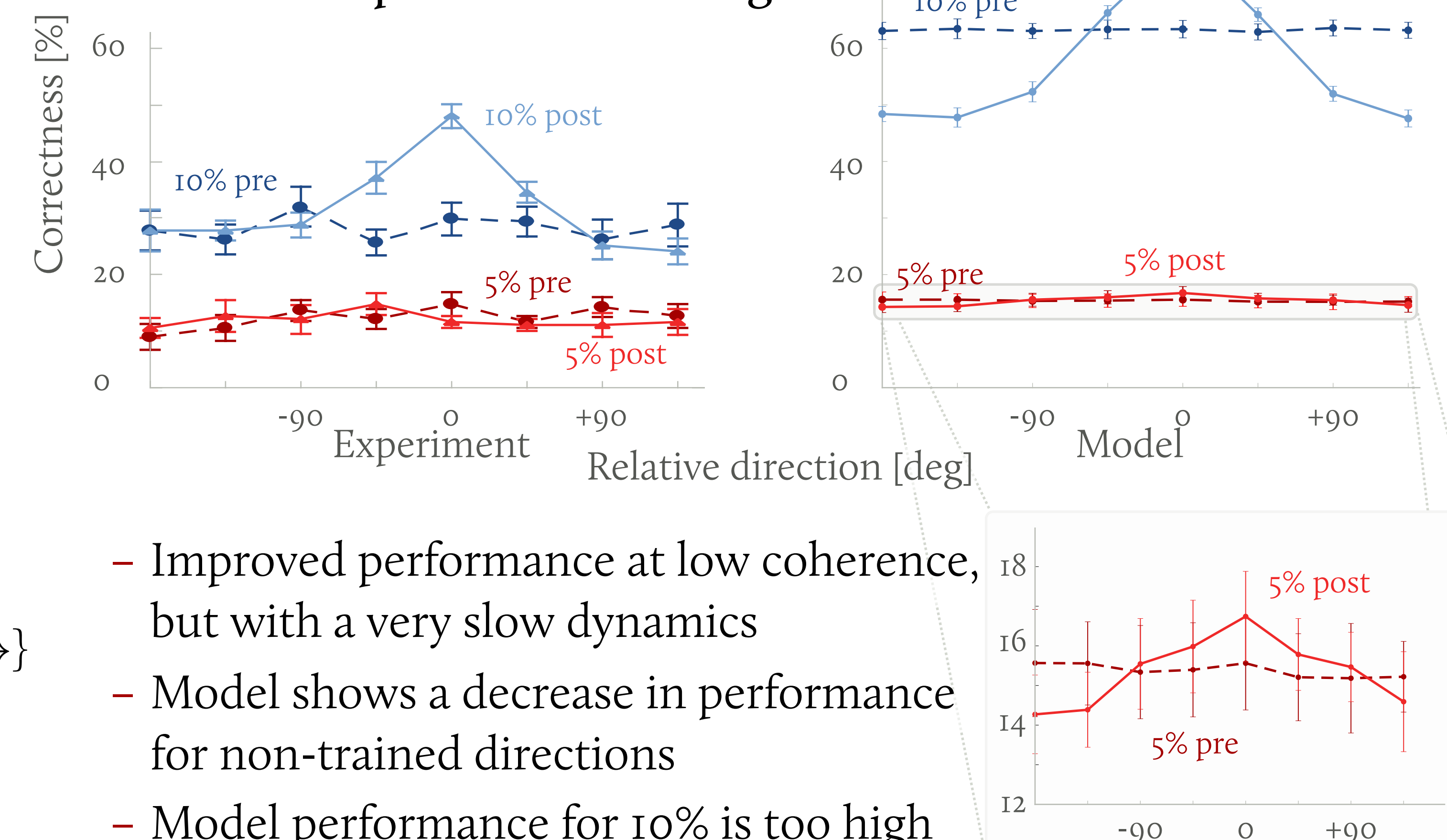
Results

Motion discrimination

First, we investigated whether and how our model can predict improved performance with practice in motion tasks. Varying the coherence level of random dots in a motion discrimination task, we show the model is always able to learn. But learning at a low coherence level is extremely slow. The model generates threshold-versus-coherence curves resembling rvc from Doshier & Lu (1998).



We applied our model on a motion discrimination task described in Watanabe et al (2001), in which subjects trained to an unattended random dot stimulus with 5% coherence (undetectable) are asked to discriminate between 8 possible directions. Results at 5% show no noticeable learning, but improvements at 10% indicate that attention and perception are not required for learning.



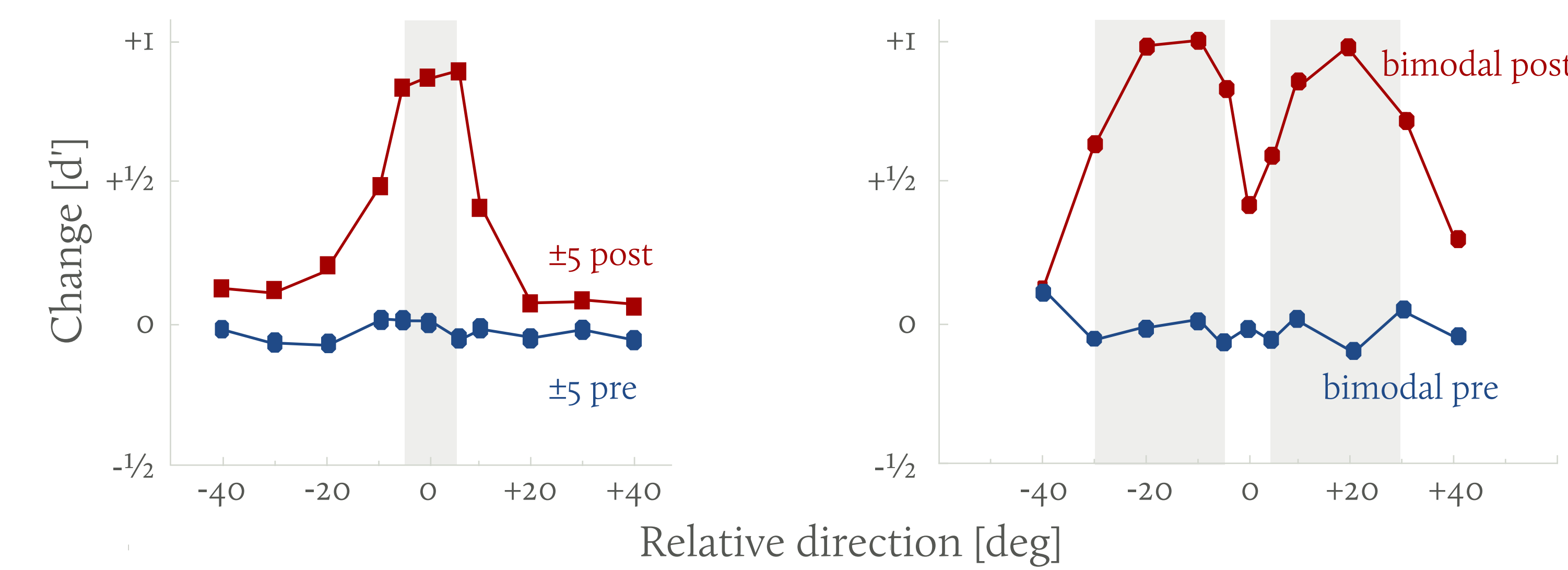
- Improved performance at low coherence, but with a very slow dynamics
- Model shows a decrease in performance for non-trained directions
- Model performance for 10% is too high

Bibliography

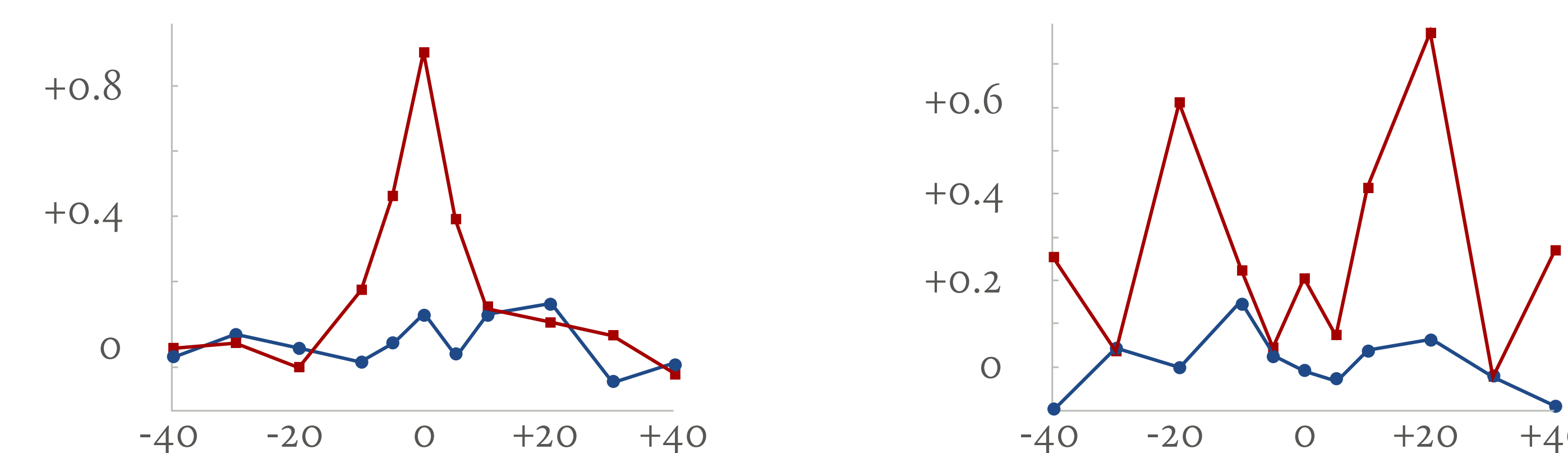
- Doshier, B.A. & Lu, Z.-L. (1998). PNAS, 95(23).
 Doshier, B.A. & Lu, Z.-L. (1999). Vision Research, 39(19).
 Mingolla, E., Todd, J.T. & Farley N.J. (1992). Vision Research, 32(6).
 Petrov, A.A, Doshier, B.A. & Lu, Z.-L. (2005). Psychological Review, 112(4).
 Petrov, A.A., Doshier, B.A. & Lu, Z.-L. (2006). Vision Research, 46(19).
 Tlapale, É., Masson, G.S. & Kornprobst, P. (2010). Vision Research, 50(17).
 Watanabe T., Náñez J.E. & Sasaki Y. (2001). Nature, 413(6858).
 Watanabe T., Náñez J.E., Koyama S., Mukai I., Liederman J. & Sasaki, Y. (2002). Nature Neuroscience, 5(10).

Motion integration

Watanabe et al (2002) studied perceptual learning in local (random dots moving within -5 to +5 degrees) and global motion perception (random dots moving within -30 to -5 and +5 to +30 degrees). They found perception learning in both cases, with performance improved for the directions matching the dot distributions, and concluded that perceptual learning occurred in the local stage of motion processing.

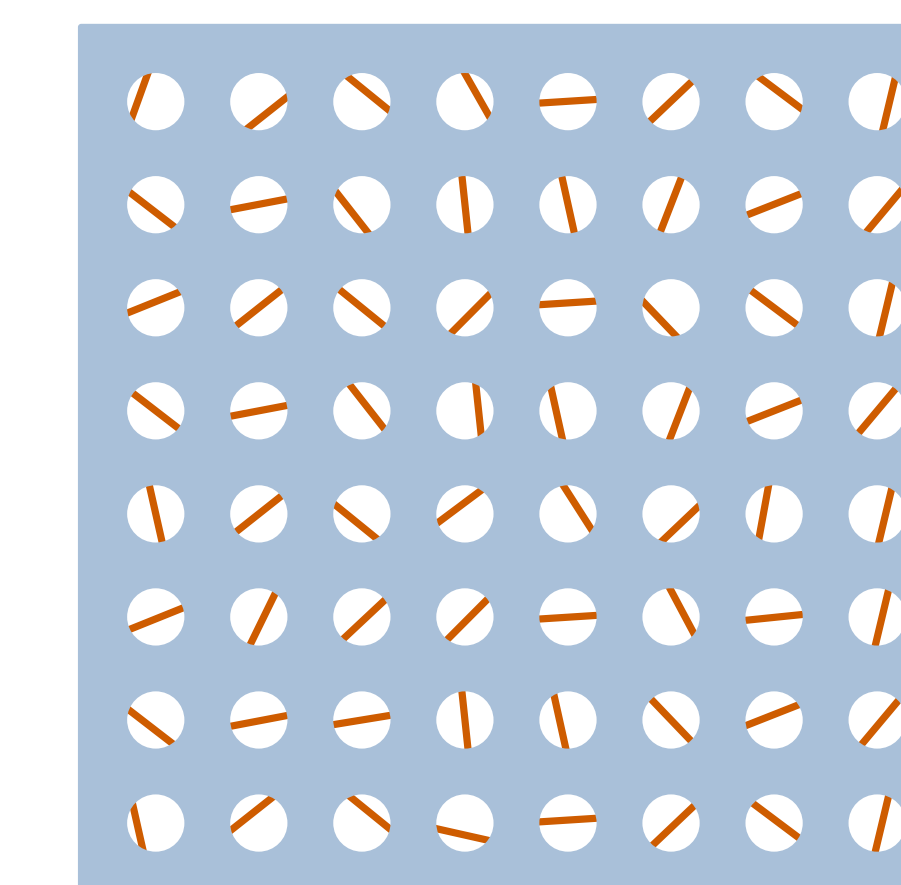


Since our global motion does not simply average local information, we are able to reproduce those results with reweighting on either F or W . We show the results for W :

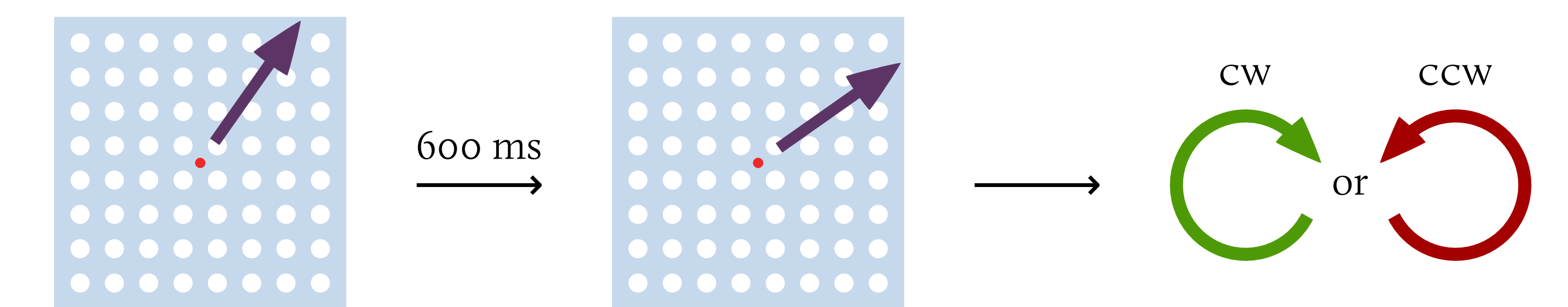


Motion aperture

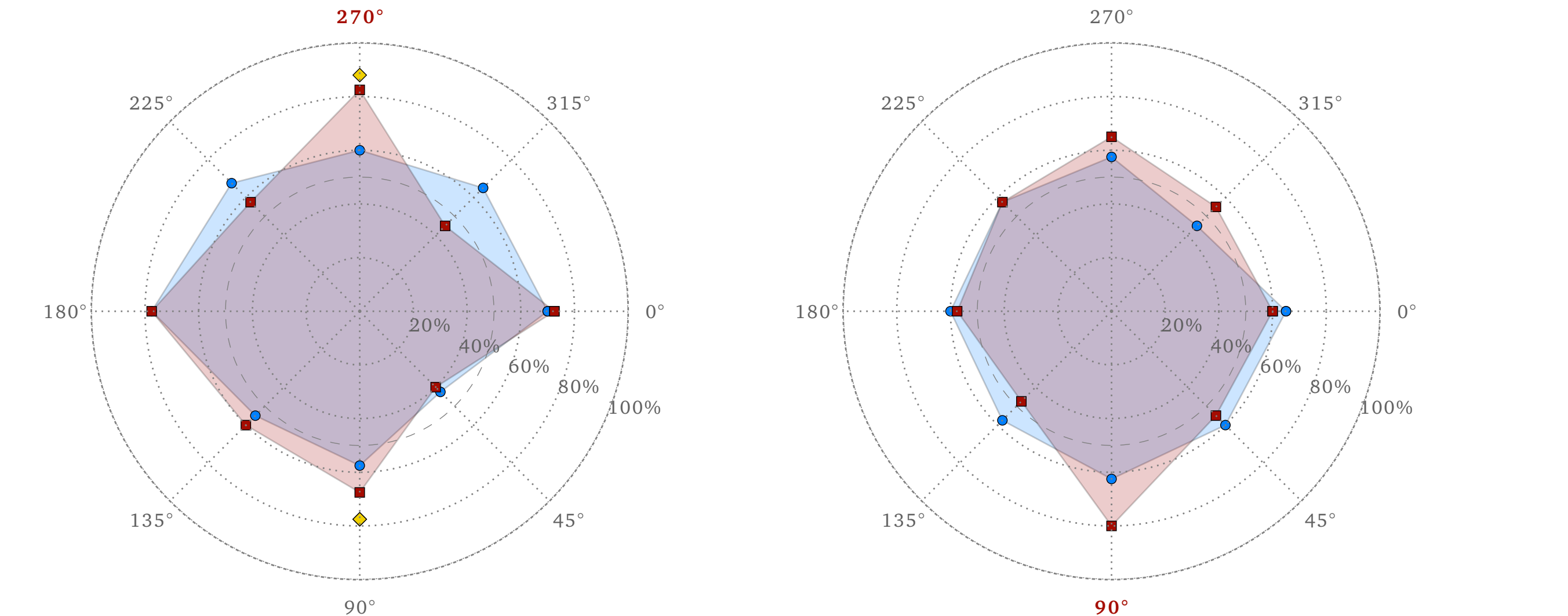
Having exhibited a model where perceptual learning can be explained through reweighting at two different locations, we proceed by designing an experiment in which those two reweighting lead to different results. With a motion aperture problem, where the true motion needs to be integrated, our model predicts no direction specific learning for reweighting in F , but a direction specific learning when reweighting occurs in W .



- | | |
|--|--|
| Like Mingolla et al (1992) | Unlike Mingolla et al (1992) |
| - Translating lines viewed behind circular apertures | - Orientations and directions span the full circle |
| - No 2D features \rightarrow integration | - Speeds coherent with aperture problem |
| - 4.5 deg/s activates V1 and MT | |



Preliminary experiments show that (some) subjects are able to learn to discriminate between such global motions, depending on initial performance level.



Discussion

We developed a new model of perceptual learning in motion tasks, combining the dynamical network model of motion processing by Tlapale et al. (2010) and the reweighting concepts (Doshier & Lu, 1998, 1999; Petrov et al, 2005, 2006) and showed that the model can reproduce the results of representative perceptual learning experiments - with alternative explanations for some experimental results obtained in the literature. We also predicted model responses to novel stimuli such as transparent motion, for which an appropriate experiment remains to be defined, and global motion, for which an experiment is being conducted.

The segregation between V1 and MT motion stages in this model accounts for a wide range of representative data with negligible feedback from higher to lower stages. Further modeling is required to determine whether feedback of motion integration signals from MT to V1 can be incorporated into these model accounts.

Acknowledgments

Supported by the National Eye Institute
Grant # EY-17491

May 2013

<http://emilien.tlapale.com/vss13>

