Exact Neural Inference Over Graphical Models

Lars E. Holzman[1] and Hava T. Siegelmann[1]

[1]U. Mass. Amherst

There is increasing neurophysical evidence that the brain performs Bayesian inference in a number of experimental paradigms including cue integration, visual scene processing, and decision making. However, as the probability distributions become more complex, it becomes more difficult to integrate out irrelevant variables to find the marginal posterior probabilities of specific variables. So, computationally, it is common to use graphical data structures to represent the dependencies between variables. We present a neural model that performs exact inference over abstract variables in graphical models. In our model, the posterior estimates of variables are proportional to the mean firing rates of idealized biologically plausible two-level neurons [1]. The relations among the variables are stored as the gain of synaptic regions and are represented as conditional probability distributions. The gains are updated incrementally using a generalized Hebbian learning rule corresponding to Bayesian updating. In this way, the neural circuit uses each evidence both to update posterior estimates of the variables quickly and to learn about the relationships between the variables over a longer time scale.

We illustrate the ability of our neural model to estimate conditional probabilities on-line and then apply the learned conditional probabilities using the cue-integration task. Humans combine location estimates formed through vision and proprioception using dimension dependent variances. A Bayesian model has been applied to this combination in, for example, Deneve and Pouget [2]. As opposed to previous works, our method allows Bayesian estimation of the modality specific distributions from the inputs. It performs a Bayesian optimal inference using the learned variances. Also, our network is significantly smaller and sparser than previous neural models of this task.

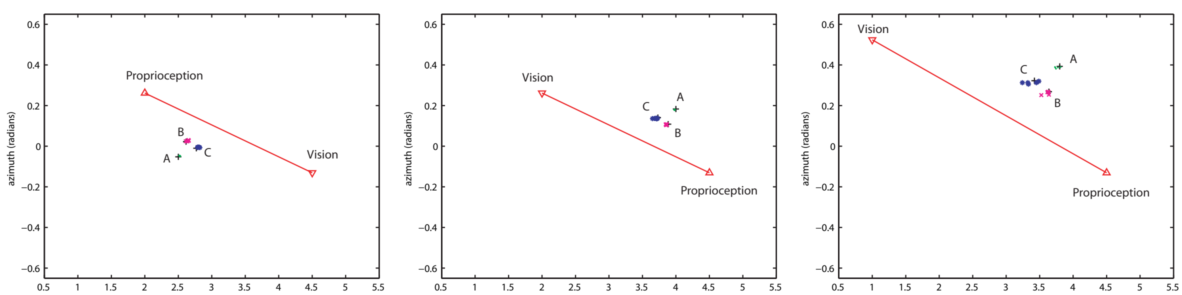

Figure 1: Results from neural inference along two perceptual dimensions: distance and azimuth. Crosses indicate the Bayesian optimal cue integration for each of three experimental conditions A, B, and C each of which have different sense/dimension dependent variances. Points indicate the output of the network clustered around the Bayesian optimal estimate.

References

[1] Pyramidal neuron as two-layer neural network. Poirazi, P., Brannon, T. & Mel, B., *Neuron* 37, 2003.

[2] Bayesian multisensory integration and cross-modal spatial links. Deneve, S. & Pouget, A., *J. Physiol.* 98, 2004.