A neural-sampling based model of early visual processing based on leaky integrate-and-fire neurons

Olshausen & Field [1], and a series of studies building on it, have shown that V1 receptive fields emerge from learning in a linear Gaussian model of natural images under a sparse sprior. How V1 neurons might implement inference in such a system is less clear, and prior work has typically assumed that network dynamics serve to find the most probable explanation of the visual inputs rather than the full posterior distribution [1,3, but see 9, 12]. Here, we derive a spiking neural network model using deterministic leaky integrate-and-fire (LIF) neurons and stochastic synapses whose responses represent binary samples from the joint posterior given a retinal input (Fig A, B). Simulating the model we find agreement with classic neurophysiological observations about V1 neurons, from approximately contrast-invariant tuning curves (Fig C) to near Poisson variability to small noise correlations with a mean of close to zero (Fig D) [6], to negative causal influences between neurons of similar receptive fields (Fig E) [7]. Recently, it was also shown that responses from such a model also form a probabilistic population code over orientation [8]. Within the context of this model we can understand the underlying cause for each observation, e.g. why near contrast-invariant orientation tuning is *not* in contradiction to a sharpening posterior over orientation with increasing contrast, or that the main contribution to near-Poisson variability are stochastic synapses, not feedforward input noise or unreliable neurons – making empirically testable predictions.

With our work we build on and extend prior results, key among them are the findings that learning in binary linear Gaussian models yields V1-like RFs [2], a proposal how sampling in discrete time may be implemented by asynchronous spikes in continuous time [10], and the proposal that a synapse's stochasticity may reflect Bayesian uncertainty about its correct value [4,13]. It complements work showing that networks of deterministic LIF neurons can sample from Boltzmann distributions with Poisson-like variability when in a high conductance regime [5]. More generally, our work bridges Marr's three levels [11], from assuming a computational goal (here, probabilistic inference over visual inputs) to an algorithm (neural sampling) to neural implementation (network of LIF neurons) (Fig A).

References

[1] Olshausen, Bruno A., and David J. Field. "Sparse coding with an overcomplete basis set: A strategy employed by V1?." Vision research 37.23 (1997): 3311-3325.

[2] Bornschein, Jörg, Marc Henniges, and Jörg Lücke. "Are V1 simple cells optimized for visual occlusions? A comparative study." PLoS computational biology 9.6 (2013): e1003062.

[3] Rozell, Christopher J., et al. "Sparse coding via thresholding and local competition in neural circuits." *Neural computation*20.10 (2008): 2526-2563.

[4] Aitchison, Laurence, and Peter E. Latham. "Synaptic sampling: A connection between PSP variability and uncertainty explains neurophysiological observations." *arXiv preprint arXiv:1505.04544* (2015).

[5] Petrovici, Mihai A., et al. "The high-conductance state enables neural sampling in networks of LIF neurons." BMC neuroscience 16.1 (2015): O2.

[6] Ecker, Alexander S., et al. "Decorrelated neuronal firing in cortical microcircuits." science 327.5965 (2010): 584-587.

[7] Chettih, Selmaan N., and Christopher D. Harvey. "Single-neuron perturbations reveal feature-specific competition in V1." Nature (2019): 1.
[8] Shivkumar, Sabyasachi, et al. "A probabilistic population code based on neural samples." Advances in Neural Information Processing Systems. 2018.
[9] Hoyer, Patrik O., and Aapo Hyvärinen. "A multi-layer sparse coding network learns contour coding from natural images." Vision research 42.12 (2002): 1593-1605.
[10] Buesing, Lars, et al. "Neural dynamics as sampling: a model for stochastic computation in recurrent networks of spiking neurons." PLoS computational biology 7.11 (2011): e1002211.
[11] Marr, David. "Vision: A computational investigation into the human representation and processing of visual information." (1982).
[12] Orbán, Gergő, et al. "Neural variability and sampling-based probabilistic representations in the visual cortex." *Neuron* 92.2 (2016): 530-543.
[13] Zhu, M., & Rozell, C. J. (2013). Visual Nonclassical Receptive Field Effects Emerge from Sparse Coding in a Dynamical System. PLoS Computational Biology, 9(8), 1–15.