Hyper-selectivity, gain control and the tuning of sensory neurons

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The non-linearities of sensory neurons have been described in a wide variety of ways using a large variety of stimuli. In this presentation, we focus on a stimulus independent description that considers the response geometry of the neuron (1,2,3). We describe two forms of selectivity in sensory neurons. The first form is the linear or “basic selectivity”. This is a traditional form of selectivity that is revealed by the classical receptive field. This receptive field will typically describe the stimulus that optimally stimulates the neuron. The second type of selectivity we describe as “hyper-selectivity” and it is either implicitly or explicitly a component of several models including sparse coding, gain control, some cascaded linear non-linear (LNL) models. Hyper-selectivity is unrelated to the stimulus that maximizes the response. Rather, it is a function of the relative drop-off in response around that optimal stimulus (i.e., a curvature in the iso-response surfaces). A neuron that is hyper-selective has an iso-response contour that falls off at a rate that is faster than a linear neuron. An invariant response is characterized by a fall off that is slower than a linear neuron. Models with hyper-selectivity allow what appear to be paradoxical results. For example, it is possible for a neuron to be very narrowly tuned (hyper selective) to a broadband stimulus. We note that the Gabor/Heisenberg limits apply to selectivity with linear neurons. However, some non-linearities can easily break this limitation and we show this with both model data published data from V1 neurons. Results with over-complete sparse codes typically focus on the linear selectivity but that the hyper-selectivity systematically increases as the network becomes more overcomplete. We find that when measured with spots or gratings the receptive fields will systematically misestimate the optimal stimulus for the neuron. For 4x overcomplete codes, we find that the difference between the optimal stimulus and the receptive field is surprisingly large. Finally, we argue that although gain control models, some linear non-linear models and sparse coding have much in common, we believe that our approach to hyper-selectivity provides a deeper understanding of why these non-linearities are present in the early visual system. We argue that the primary goal of gain control behavior is not to control gain.

References

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