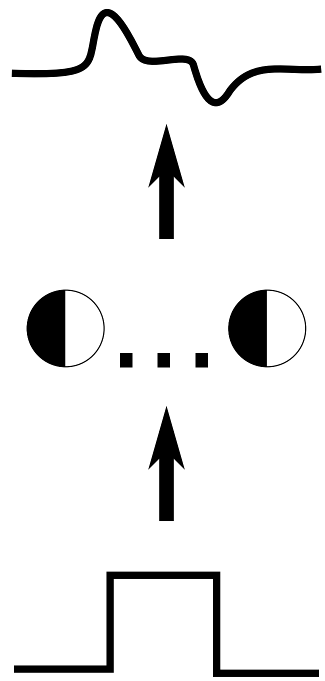
System Description



This implementation of a simple cell is a one-dimensional loop version of a distance-dependent shunting network with an odd-symmetric difference-of-Gaussians kernel. The network is solved at equilibrium. The formulation comes from (Grossberg and Todorović, 1988).

Unpacking this list of descriptors, one-dimensional loop structure means the network contains a single chain of nodes, arranged in a continuous circle. Thus, the left edge of the network actually wraps around to the right side of the network. This is only one method to deal with edge effects. Anther typical method is to pad the input with zeros or a constant value. Real-world image processing or visual tasks typically require a two-dimensional geometry, but all of the basic qualitative points of the network remain identical in higher dimensions.

An odd-symmetric difference-of-Gaussian (DOG) kernel is the element used to model a cortical simple cell. Such neurons are sensitive to edges of a specific orientation and contrast polarity. Taking a Gaussian curve, shifting it to one direction, then subtracting this new curve from the original forms an odd-symmetric DOG kernel. When used to specify the structure of input connections to a neural network, such a kernel yields network nodes with properties very similar to cortical simple cells.

A distance-dependent shunting network is a specific class of neural network. These networks have nodes with inputs coming from a limited spatial neighborhood and are defined by a specific type of differential equation. The most important effect of the shunting nature of the nodes is bounded output. No matter the intensity of the input, the nodes cannot generate an output outside the range [-1,1]. The closer the output of a given node gets to one of these boundaries, the more difficult it becomes to push the node even closer. This translates to asymptotic behavior at -1 and 1.

When presented with an input constant in time, each node in this class of network converges to a meaningful steady-state value. As long as the input is constant, it isn't necessary to numerically integrate the system of differential equation to find the steady-state solutions. Instead, one can compute an analytic solution for the steady-state behavior. This is what it means to say the network is solved at equilibrium.

See the tutorial document or the original paper for more detail on the behavior of this network.

Reference

Grossberg and Todorović. Neural dynamics of 1-D and 2-D brightness perception: a unified model of classical and recent phenomena. Perception & psychophysics (1988) vol. 43 (3) pp. 241-77