Spatial Synaptic Growth and Removal for Learning Individual Receptive Field Structures

Michael Teichmann, Fred H. Hamker

One challenge in creating neural models of the visual system is the appropriate definition of the connectivity. The modeler constrains the results with its definition, also for learning models. Using too few connections neurons will not develop appropriate receptive fields. Using too many the model might lose features like retinotopic organization. Further, often the precise knowledge about appropriate connection sizes is lacked, for instance in deeper layers of the cortex or for different neuron types like interneurons. Furthermore, also within the same population of neurons receptive field sizes can largely differ. Hence, a mechanism at hand refining the connection structure based on the learned weights would be appreciated.

Such a mechanism can be found in the human brain by structural plasticity. That is, the formation and removal of synapses (Butz et al., 2009, Brain Res Rev.; Holtmaat & Svoboda, 2009, Nat. Rev. Neurosci.). For our model, we exploit that synaptic connections are likely to be formed in the proximity of other synapses and that synapse removal is related to the stability of the spine forming the synapse (Yasumatsu et al., 2008, J. Neurosci.). If the spine volume (related to the synapse strength) is small, the spine is likely to disappear. We implemented these mechanisms as probabilistic processes. The probability for synapse formation is determined by the strength of the neighboring synapses within a certain distance (Fig. 1). The removal of synapses depends solely on the weight strength. Weak weights have much higher removal probabilities than strong ones.

We demonstrate the functioning of these mechanisms in a model of the visual areas V1 and V2 (Fig. 2), trained on natural scenes. The model learns biologically plausible receptive field structures. From its initial connection structures, it develops connection matrices closely fitting the learned receptive field of each individual neuron (Fig. 3,4). We show that connections grow and retract with learning and, thus, the receptive field is not restricted to its initial boundaries. Nevertheless, the initial retinotopic organization of the model neurons is preserved. Additionally, we tested the ability to overcome the modeler's bias by setting the initial connection matrix to the half, three fourth, and five forth of its original size (one extent) and measured the learned receptive field sizes. We found that all versions develop, independently from the starting conditions, similar receptive field sizes. Hence, we suggest structural plasticity as suitable mechanism for learning diverse individual receptive field structures while overcoming the modeler's bias.

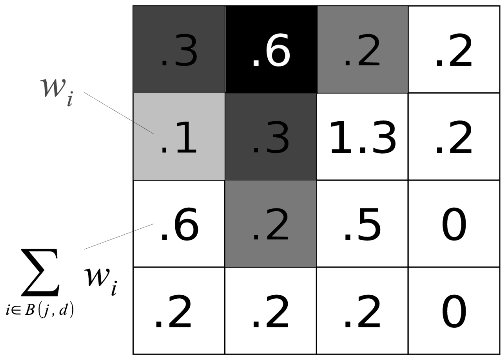

Figure 1: Factors for the build probabilities in the neighborhood of existing synapses. The sum of neighboring weights mainly determine the build probability. Values in gray shaded boxes denote weight strengths of existing synapses. Values in white boxes denote the sum of neighboring weights for non-existing synapses. Potential synapses surrounded by strong synapses will receive higher build probabilities than others.

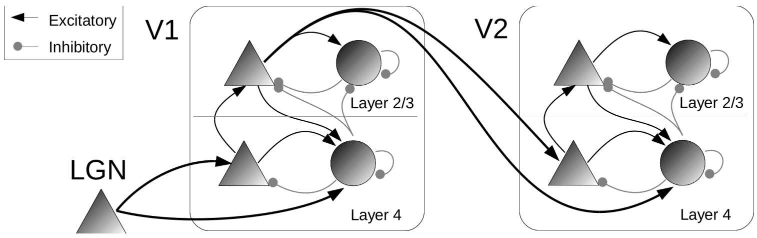

Figure 2: Model architecture. The model consists of the areas V1 and V2, having the layers 4 and 2/3. Each layer contains populations of excitatory and inhibitory neurons with emanating connections of the same type. All neurons and connections are plastic, using Hebbian or anti-Hebbian plasticity, intrinsic plasticity, and structural plasticity.

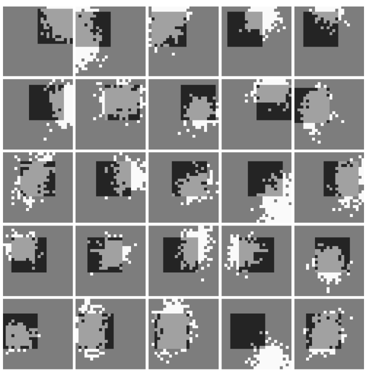

Figure 3: Initial connection matrix (dark square) and final connection matrix (bright dots) of 25 V1-L4 neurons (gray tiles).

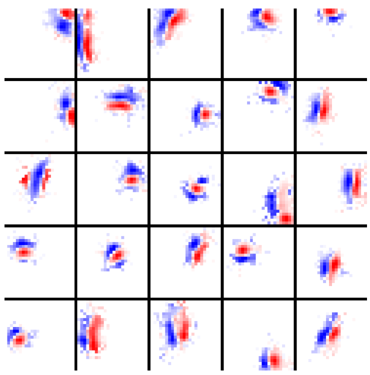

Figure 4: Learned receptive fields of 25 V1-L4 neurons, where red colors denote connections to LGN on-center neurons and blue to off-center neurons.