Introduction

The structure of orientation maps, has been shown to maintain the length of horizontal connections in V1, given certain connection patterns as a function of orientation differences. We take a V1 model network with horizontal connections.

Neuronal Activations are maintained in this network by recurrent computations constraining an associator network.

Weight Learning has been performed by using a simple mechanism for the network's neural representation of natural image patches.

Neuronal Shifting is performed here to move the moving the length of horizontal connections in a realistic orientation map. After convergence, horizontal-field directed neuron flows are in balance:

The resulting field pattern and its 2D pixel input image show the neuron's average topography and form an orientation map similar to one hypercolumn in V1.

The hidden units' activations $z_t$ are determined by the data and the lower level network. If any two units tend to fire together, this will in the following influence $W_{ij}$ via learning.

Neural Activation

The attractor network with weights $W_{ij}$ learns to maintain the input $z_t$ in its continuous activations $~z_t$. The learning rule of $\Delta W_{ij}$ is for the next time step $t+1$:

$$\Delta W_{ij} = \eta \cdot (z_t \cdot z_j - w_{ij} \cdot z_t \cdot z_j)$$

Learning sets the difference between the bottom-up input and the attractor network activations. The attractor network tries to remember the bottom-up input as good as possible. If during relaxation time the bottom-up input changes slightly, then activations can be built into the attractor network.

The background behind these ideas have shown the bottom lateral weights.

The learnt horizontal network weights are in the following interpreted as physical connections which start a forces between any two mutually connected units.

Neuronal Shifting

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Weight Learning

The hidden units' activations $z_t$ are determined by the data and the lower level network. If any two units tend to fire together, this will in the following influence $W_{ij}$ via learning.

The blue color of each neuron denotes the X-position of the receptive field.

The color of each neuron denotes its orientation.

The color of each neuron denotes its orientation tuning.

The image sequences below show neuron-shifting to binary positions.

Activation update

$$z_{t+1} = \sigma(W \cdot z_t)$$

The activation update equations are initialized with the output of the model's simple cells.

Lateral weight learning

$$\Delta W_{ij} = (z_t \cdot z_j - W_{ij} \cdot z_t \cdot z_j)$$

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Cost function

$$E = \frac{1}{2} \sum_{i,j} |z_t \cdot z_j - W_{ij} \cdot z_t \cdot z_j|^2$$

where $E_t = E - E_{t-1}$ and $\eta = \frac{\partial E}{\partial W_{ij}}$.

Hence we have $\Delta W_{ij} = -\eta \cdot E_{t-1}$. In shifting the neuron's positions we minimize the cost function by gradient descent.

Discussion

In order to maintain horizontal weight length, similar neuron shift together. Neurons are similar to a receptive field position and orientation tuning.

The number of neurons, and the receptive field size correspond to a structure no larger than a "hyper-column" in V1. Therefore we are not able to see larger structures such as patterned orientation maps.

Whether the resulting map structures likely reality, depends on (i) the lateral weights and (ii) the forces. Since the forces are straightforward to implement, rather the lateral weights are refined, and how they are learned.

Therefore this method can be used to build realistic lateral weights, and their learning rules, may be realistic.

Our current model learns to do the horizontal connections through. However, we assume that realistic neurons would be possibly similar in lateral forces, and that in the biological system, all forces must be in balance.

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