Searching for an IT model with columnar organization

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Abstract

The inferotemporal visual cortex (IT) is at the top of the 'what' stream. Cells in IT are known to respond to complex features and have a columnar organization; nearby columns prefer stimuli with similar critical features. This research demonstrates that a hill-climbing search strategy can discover a model of IT that exhibits columnar organization. This is a first step towards a more complete model of IT exhibiting translation and scale invariance. Inspired by others who have used search techniques to adjust neurocomputational model parameters successfully, this work further demonstrates the benefit of search methods in computational neuroscience.

Summary

Hill-climbing, a search strategy which always chooses to go up-hill with respect to some quality measure, was used to search for a set of parameters that would develop models of IT with a columnar organization.

The network

The network is similar to the biologically plausible self-organizing map used by Sirosh and Miikkulainen (1996) to model column formation in primary visual cortex. A mean-firing rate neural model was chosen. A small (1 by 10 excitatory and 1 by 10 inhibitory neurons) IT network was used to allow the search algorithm to complete in several hours time on a 1.8 GHz Pentium 4 processor. Each excitatory neuron received input from a common 20 by 20 visual area. The excitatory and inhibitory IT neurons were reciprocally connected. The firing rate of each neuron is calculated as follows:

$$\mathbf{f}(t+1) = \tanh(p\,\mathbf{f}(t) + (1-p)(c_{input}\,\mathbf{w}_{input}\cdot\mathbf{x} + c_{inhib}\,\mathbf{w}_{inhib}\cdot\mathbf{f}(t) + c_{recurrent}\,\mathbf{w}_{recurrent}\cdot\mathbf{f}(t))-\theta)$$

where c_{conn_type} is the connection influence for connection type *conn_type*, θ is the threshold, and w_{conn_type} is the weight vector for connection type *conn_type*. Weights were updated after each cycle with the following formula:

$$\mathbf{w}(t+1) = \mathbf{w}(t) + \alpha\mathbf{x}(t)$$

where $\mathbf{x}(t)$ represents either the visual input, inhibitory input, or recurrent input depending on the connection type. The learning rate, α, was set independently for each connection type. Each connection type was normalized independently such that the weight vectors had unit length.

Training

In order to evaluate the quality of a given network, three training runs were made with the same parameter settings, but different random number seeds and training sequences. Two training stimuli is the minimum number required to demonstrate columnar organization. Diamonds and squares were used in the experiments. Each stimulus was presented to the network for 4 consecutive cycles before randomly switching to a new stimulus. A blank image was presented to the network for two cycles between each stimulus. Each stimulus was presented to the network an equal number of times. Networks were trained for 100 total cycles during each training run. The network quality was evaluated based on the response of the network during the 100 training cycles as described next.

Searching

The search algorithm set the following network parameters. Search ranges are shown in brackets.
Neuron parameters: threshold (θ) [0, 1] and persistence (p) [0,1]
Connection parameters: connection radius [0, 6], learning rate (α) [0, 0.1], and connection influence (c) [0, 1].

Since the same parameters applied to all neurons of the same type, the number of parameters is independent of the number of neurons in IT. Therefore this method should apply to larger, two-dimensional, networks.

Automated search requires a method of generating new candidate networks and a function to evaluate candidates. New parameters were generated each iteration by randomly modifying the best network found thus far. A Cauchy random number generator was used in order to concentrate the search around the existing solution while allowing for occasional large jumps. In addition, the standard deviation of the distribution was inversely proportional to the search cycle (0.25 at the beginning, and 0.05 at the end).

Once a new candidate network was generated, a quality metric was applied. Only improvements in quality were accepted. The quality measure, q, for a single training run was defined as

$$q=\Sigma_{i\in S}\, m_i + \Pi_{i\in S}\, m_i$$

where S is the set of all stimulus patterns (2 in this case), and m_i is the winning margin for stimulus i:

$$m_i = g(\Sigma_{t\in I} f(t) - \Sigma_{t\notin I} f(t))$$

where I is the set of all time steps with input stimulus i, and g(x) is half-wave rectification. The function q encourages networks with cells which respond strongly to only a few stimuli, but yet respond to all of the stimuli. The second term is maximized when the winning margins for each category are equal, rewarding networks which divide up the neurons in proportion to the input stimulus distribution.

Results

The search algorithm was allowed to run until 2,000 networks had been evaluated. The best set of network parameters are given in the following tables:

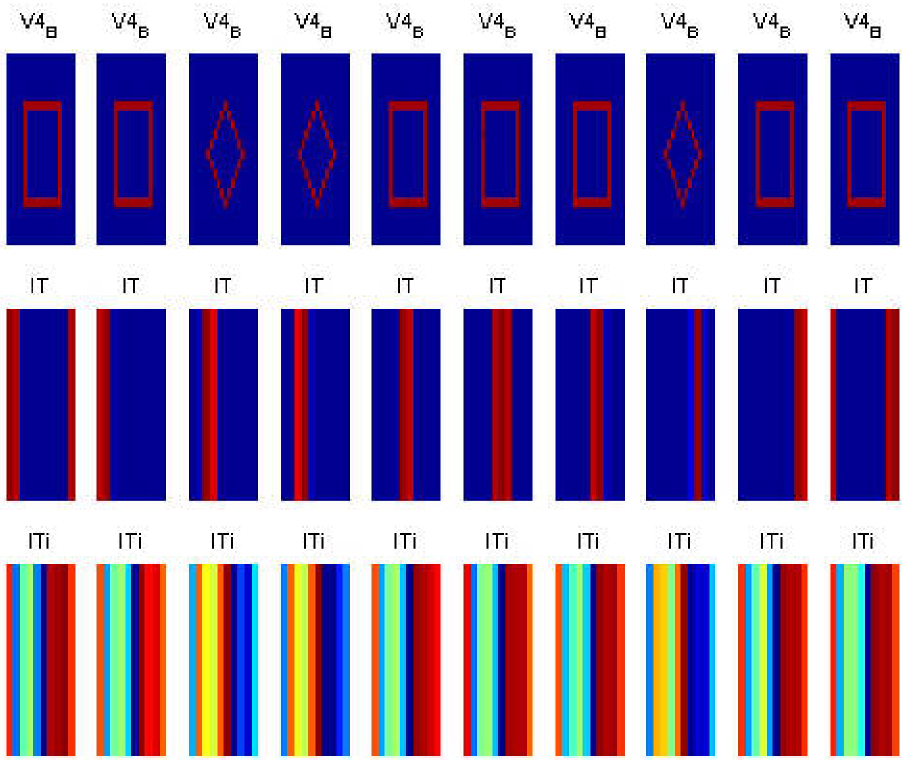
Neuron parameters

Area	Threshold	Persistence
IT_e	1	0.15
IT_i	0	0.23

Connection parameters: (connection radius, connection influence, and learning rate)

To\From	IT_e	IT_i	Visual Input
IT_e	1, 0.16, 0.1	5,-1, 0.09	N/A, 1, 0.1
IT_i	2, 0.84, 0.01	2, -0.1, 0.01	N/A,N/A,N/A

This network exhibits a columnar organization, as shown in the figure below.



The figure shows the weights for all input connections for each of the 10 neurons in IT, where red is maximum and blue is the minimum value. Neurons that prefer the same stimulus cluster together (see the first row showing connections to the visual input area), and that after training, each neuron responds to a particular input pattern. In addition, the network divides up the neurons such that some respond to each pattern rather than all responding to the same stimulus.

Several counterintuitive parameters settings were found to maximize the quality measure. One is the fact that it was beneficial for the inhibitory neurons to learn the connection strengths from both the excitatory neurons and other inhibitory neurons. The paper will further analyze the parameters discovered by the algorithm in order to assess their importance for the success of the network.

References

Sirosh, J., Miikkulainen, R. (1996). Self-organization and Functional Role of Lateral Conmnections and Multisize Receptive Fields in the Primary Visual Cortex. *Neural Processing Letters*, 3:39-48.