The Neural Representation of Spatial Relationships by Anatomical Binding

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VSS May 2010

Introduction:

Many theorists have hypothesized that when viewing a multi-object scene, the visual system assigns each object’s bounded features to separate "slots". Such dynamic "binding" to multiple slots is at the heart of the Object File Theory (Kahneman, Treisman & Gibbs 1990), Visual Short-Term Memory (VSTM) models, FINST Theory (Pylyshyn 1989), Recognition-By-Components theory (Biederman 1987) and others.

It is an open question how such "slots" are implemented neurally. We have suggested that such slots are actually implemented as separate populations of neurons in ventral visual areas. We call this "Anatomical Binding" and have developed a model of the visual system called the Multiple Slots Multiple Spotlights (MS2) model based on this hypothesis.

A key prediction of such anatomical binding is that a wide range of scene manipulations should produce no change in the neural representation coding that scene.

In contrast, certain scene manipulations will produce a disproportionately large change in neural representation:

1. The (MS)2 model contains two (or more) independent feature hierarchies each with its own spotlight of attention and is thus able to represent two objects simultaneously on separate “slots” of neurons.

2. The (MS)2 model’s slot representation is completely compatible with the ACT-R slot-based cognitive architecture — allowing for direct storage of visual percepts into declarative memory, direct comparison of visual inputs with other buffers, and direct control of the multiple Spotlights. This link to ACT-R can begin to explain our fantastic ability to process complex visual relationships (for example, reading a building blueprint).

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Addressing the key theoretical question raised by the (MS)2 model:

Question: “How can higher brain centers ‘understand’ a pattern of neural firing on Slot#1 neurons and a different pattern of neural firing on Slot#2 neurons both represent the same object concept (for example the capital letter ‘A’)?”

Answer:

To address this concern we must have a model of the “higher brain centers” that will be interpreting the output of the visual system.

By far the most complete model of the human cognitive architecture is the ACT-R model (Anderson 2007):

Even if the letter ‘A’ is represented by different patterns of neural firing in Slot#1 and Slot#2, as long as the cognitive architecture can correctly perform the operations of between slot equality comparison and between slot transfer, then from the system’s point of view those slots contain the same symbol.

This “symbol meaning consistency” can be accomplished with the following neural implementation of slots and the following training regime...

Between Slot Comparison

Between Slot Transfer

Conclusions:

1. The (MS)2 model contains two (or more) independent feature hierarchies which each has its own spotlight of attention and is thus able to represent two objects simultaneously on separate “slots” of neurons.

2. This model allows simultaneous representation of two objects for the training of a network that codes for a wide range of complex visual relationships (e.g. top-of, parallel, same size, etc.)

3. The (MS)2 model’s slot representation is completely compatible with the ACT-R slot-based cognitive architecture — allowing for direct storage of visual percepts into declarative memory, direct comparison of visual inputs with other buffers, and direct control of the multiple Spotlights. This link to ACT-R can begin to explain our fantastic ability to process complex visual relationships (for example, reading a building blueprint).

We have mathematically shown that given the proper neural implementation of slots and the proper training regime, the crucial operations of slot comparison and slot transfer can be performed in a way that ensures “symbol meaning consistency” between all slots.