# ONTOGENETIC DEVELOPMENT OF BEHAVIOR FOR SIMPLE TASKS

DEREK HARTER and ROBERT KOZMA
Department of Mathematical Sciences
University of Memphis
Memphis, TN 38152, USA
Tel: (901)678-2482, Fax:(901)678-2480
email: {dharter,rkozma}@memphis.edu

**ABSTRACT**
The development of complex adaptive behavior in biological organisms represents vast improvement over current methods of learning for artificial autonomous systems. Dynamical and embodied models of cognition [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11] are beginning to provide new insights into how the chaotic, non-linear dynamics of heterogeneous neural structures may self-organize in order to develop effective patterns of behavior. We are interested in creating models of ontogenetic development that capture some of the flexibility and power of biological systems. In this paper we present a simple task environment that is complex enough for people to exhibit examples of the type of development we are interested in. We describe some results of standard neural networks in performing this task. And we discuss future plans for models that display the development of effective behavior in the task environment.

**KEY WORDS**
Adaptive Intelligent Systems, Ontogenetic Development, Dynamics

## 1. Introduction

The development of behavior in biological organisms is primarily a self-organizing phenomenon. Organisms are born with a basic repertoire of motor skills and instinctive drives and needs. These are often tied to simple action-loops [1], which provide a basic repertoire of pattern completion and instinctive behavior that can begin to satisfy the intrinsic drives of the organism. As the organism develops both physically and behaviorally, however, these instinctive behavior patterns begin to be associated with more general sensory stimuli. The organism learns to recognize patterns in the environment that are important and useful affordances [12] for beneficial behaviors. Increasingly complex patterns of behavior are hierarchically organized around the solutions that are discovered at earlier stages of development.

Thelen and Smith [11] view development as a shifting ontogenetic landscape of attractor basins. As physical and behavioral patterns develop the landscape is continually reformed and reshaped. Each developed behavior opens up many possibilities for new, more complex patterns of behavior, while closing off possibilities for others. Even relatively simple tasks can provide opportunities for the hierarchical development of increasingly complex strategies in order to improve performance. For example, in the simple task we present in the next section, humans develop higher level strategies for improving their performance.

Many theories of the development of behavior in biological organisms are beginning to view it in terms of a self-organizing dynamical system [7, 8, 11]. The organization of patterns of behavior is viewed, in some sense, as the formation and evolution of attractor landscapes. Some research [10, 4, 5, 6, 9] also indicates that chaotic dynamics may play an essential role in the formation of perception and behavior in biological organisms.

## 2. Packing Task

Towards the end of studying and creating models of development, we have begun work on identifying and creating appropriate task domains. These tasks need to be both simple and tractable for realistic computational models of development. However they must also support examples of the development of behavior from novice to expert in humans of the type we are interested in. We describe a packing task here which is one such environment, and some work on standard machine learning tools in this environment.

### 2..1 Description

In the packing task, which is a simplified form of the Tetris game [13, 14], the system can be presented with one of 3 shapes. The goal of the task is to move and rotate a shape before allowing it to drop onto a playing field in such a way as to end up with as compact of a packing as possible. An example of a packing trial in progress can be found in figure 1. In our version of the

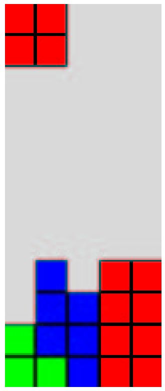

Figure 1. An example packing task trial

packing task, the system is given a random sequence of 10 shapes. The performance of the system on the packing task is evaluated by examining the density and the height of the resulting packing of those 10 shapes.

## 2..2 Encoding

We now present an example of a standard neural network that learns to perform the simple packing task. The neural network needs to be given some sense of the current state of the environment. For the experiments performed here, two pieces of input were given to the network: the type of shape that has appeared, and a perception of the contours of the current playing field. The system provided two outputs: where to position the shape and how to rotate or orient the shape before dropping it.

## 2..3 Training

We trained standard backpropogation neural networks using the encoding described above. For training data we had a human perform 50 packing trials, and we captured and encoded the input and the output of the behavior that the human produced when performing the packing task. We trained and tested the networks with many different configurations of number of hidden nodes and training epochs. We then chose the best configurations in order to evaluate the performance of the networks on the packing task.

## 2..4 Experiments

We used our packing task testbed in order to evaluate the performance of the networks on simulated packing trials. We gave the networks 100 random trials and measured their performance by calculating the packing density and height that they achieved. Packing height is simply a measure of the highest column of blocks in the playing field. Packing density is measured by looking at the ratio of the number of filled spaces in the packing to the total area of the packing. In figure 1 the packing has a height of 4 and a density of 17 / 20 or 0.85. Lower heights and higher densities indicate better performances on the task.

Table 1. Comparison of average height and density performance measures on 100 simulated packing tasks

| | Height | Density |
|---|---|---|
| Human | 7.62 | 0.8748 |
| Neural Network | 8.18 | 0.8261 |

## 2..5 Results

A human learned the packing task and was asked to perform 100 trials. Similarly the resulting neural networks were run for 100 trials. Table 1 shows a comparison of the average performance on 100 trials by a typical neural network and the human. Figure 2 shows a histogram of the performance of the human and the neural network rated by height and density.

# 3. Development of Behavior in the Packing Task

Basic neural networks perform adequately on the packing task, but obviously are not quite as good at packing as humans. Even for this simplified task humans alter their strategies as the task progresses. Early on in a packing trial, a human is willing to wait for optimal fits. People know intuitively that, even though they see shape types at random, they are likely to see the particular shape type needed for a perfect fit if it is still early in the trial. However, as the trial progresses, strategies shift to those that will simply minimize the height of the packing.

The development of differing strategies given the context of the problem, not to mention the recognition that evolving contexts afford for behavior, is a prime example of the development of skills in biological organisms. People are not given explicit examples of appropriate shifts in strategies. They develop such strategies by interacting with the task environment, and guided by their previous experience with the constraints of the problem. They seem to quickly and intuitively embody the opportunities that situations afford for good behaviors, and how such opportunities change with the changing situation. In other words, they develop a set of skills and strategies for improving their performance on the problem simply through interaction and experience in the task domain.

Even in our simple environment we see that people develop differing strategies for behavior based on the context of the progress of the trial. For example,

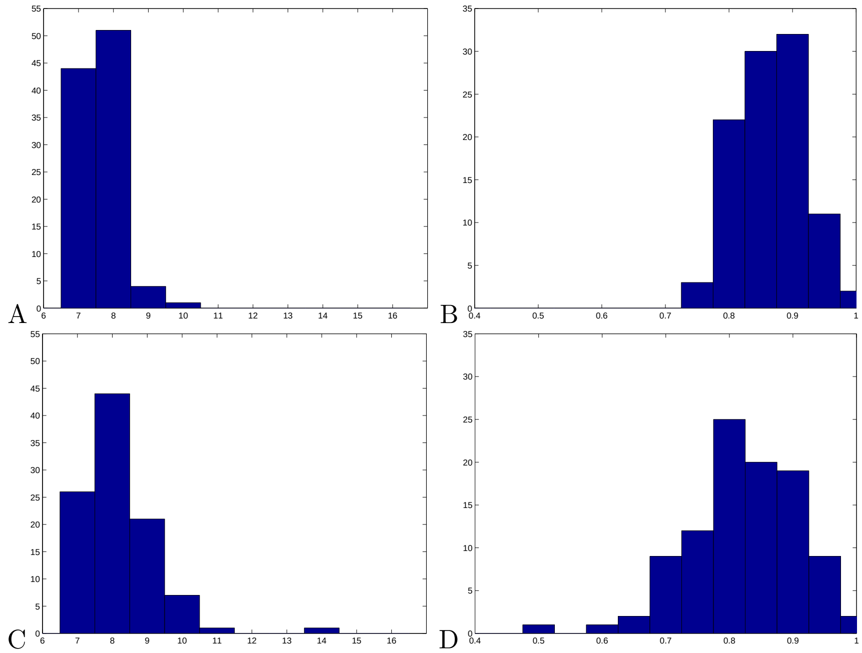


Figure 2. Histograms of performance on 100 trials of the packing task. The top two figures (A and B) show the performance of a human subject in the packing task, while the bottom two (C and D) display the performance of a neural network. In the left column we are measuring performance by the height of the packing. On the right we show performance by the density of the packing.

humans first learn a basic set of good contours and correspondence with different shape types that provide for efficient packings. From this basic set of behavior, they begin to develop preferences for patterns that keep open future opportunities. Some contours naturally accommodate more than one shape type, and are preferred over other patterns that limit good packing to a single shape type. Furthermore, people begin to develop higher level strategies at this point. For example, if it is early in the trial they wait for more optimal packings, but later on they simply try and minimize the height. The challenge in creating models of development is in capturing this ability to, not only softly assemble solutions through a repertoire of learned and innate skills, but to also develop new skills and effective higher level strategies for the problem domain.

## 4. Future Directions

The basic neural networks presented here are not quite capable of human level performance in the packing task. The primary reason for this deficiency is an inability to perceive the changes in circumstances that cause a shift in the behavior of the human trainers. We have no doubt that adding on more contextual input (such as the current height of the packing, or a count of the number of shapes packed so far) would improve the performance of the basic network, though it remains to be seen if it could equal human performance. Also, other methods such as recurrent, dynamical neural networks, or genetic algorithm optimizations, should be capable of bringing standard methods of machine learning up to human level performance on this simple task.

The point is not to equal human performance in this simplified domain, but to begin to create models that can develop behavior on their own in a cognitively plausible manner, and that display some of the flexibility of biological development. Most standard methods of machine learning should be able to competently handle the packing task environment in its simplified form but inevitably will break down as we add complexity and real time constraints to the task.

KIII is a dynamical memory device, which has been used successfully to solve difficult classification problems in vague, and noisy environments [9]. The KIII model incorporates several KII sets, which can be interpreted as units generating limit cycle oscillations in an autonomous regime. High-dimensional aperiodic and chaotic behavior does not emerge until the complete KIII system is formed. KIII has a multi-layer architecture with excitatory and inhibitory lateral, feedforward, and feedback connections. KIII models can grasp the essence of the observed dynamic behavior in certain biological neural networks. It seems feasible to build a simplified version of KIII for the action selection task addressed in this work. We call it 3*KII model, as it consists of 3 mutually interconnected KII sets. Each KII set has a well-defined oscillation frequency. The complete 3*KII model, however, may exhibit high-dimensional, aperiodic oscillations as the result of competing, incommensurate frequencies of the KII components.

The advantage of 3*KII is that it allows a self-organized encoding of behavioral patterns into localized wings of a high-dimensional attractor. Therefore, we can obtain flexible and noise-resistant transitions among the states of the system, self-organized into a sequence of elementary actions of phase transitions. It is expected that by defining a more challenging packing task with a larger number and more complicated set of block patterns and also a larger playing field; the application of a dynamical encoding and action selection mechanism such as 3*KII would prove to be beneficial. Also the emergence of self-organized action patterns would be imminent and complex behavioral patterns could be generated and studied.

## 5. Conclusion

The development of behavior, even in a simplified environment such as the packing task, can shed light on the mechanisms of biological development and learning. Biological organisms are able to effectively develop increasingly complex skills and strategies simply by interacting with and solving problems in their environment. The dynamic, self-organization of behavior in biological organisms is a powerful model of learning that, if better understood, would provide great opportunities for improved artificial behaving and learning systems. Development of behavior in biological organisms can be viewed as a self-organizing dynamical system. Some research also indicates the importance of chaotic modes of organization in the development of behavior.

## References


[1] Andy Clark. *Being There: Putting Brain, Body, and World Together Again.* (Cambridge, MA: The MIT Press, 1997).

[2] Gerald M. Edelman and Giulio Tononi. *A Universe of Consciousness: How Matter Becomes Imagination.* (New York, NY: Basic Books, 2000).

[3] Stanley P. Franklin. *Artificial Minds.* (Cambridge, MA: The MIT Press, 1995).

[4] Walter J. Freeman. *How Brains Make Up Their Minds.* (London: Weidenfeld & Nicolson, 1999).

[5] Walter J. Freeman and Robert Kozma. Local-global interactions and the role of mesoscopic (intermediate-range) elements in brain dynamics. *Behavioral and Brain Sciences*, 23(3), 2000.

[6] Walter J. Freeman, Robert Kozma, and Paul J. Werbos. Biocomplexity: Adaptive behavior in complex stochastic dynamical systems. *BioSystems*, 2000.

[7] Horst Hendriks-Jansen. *Catching Ourselves in the Act: Situated Activity, Interactive Emergence, Evolution and Human Thought.* (Cambridge, MA: The MIT Press, 1996).

[8] J. A. Scott Kelso. *Dynamic Patterns: The Self-organization of Brain and Behavior.* (Cambridge, MA: The MIT Press, 1995).

[9] Robert Kozma and Walter J. Freeman. Chaotic resonance - methods and applications for robust classification of noisy and variable patterns. *International Journal of Bifurcation and Chaos*, 11(6), 2001.

[10] Christine A. Skarda and Walter J. Freeman. How brains make chaos in order to make sense of the world. *Behavioral and Brain Sciences*, 10, 1987, 161–195.

[11] Esther Thelen and Linda B. Smith. *A Dynamic Systems Approach to the Development of Cognition and Action.* (Cambridge, MA: The MIT Press, 1994).

[12] J. J. Gibson. *The Ecological Approach to Visual Perception.* (Houghton Mifflin, 1979).

[13] David Kirsh and Paul Maglio. Reaction and reflection in tetris. In J. Hendler, editor, *Artificial Intelligence Planning Systems: Proceedings of the First Annual International Conference (AIPS92)*, San Mateo, USA, 1992.

[14] David Kirsh and Paul Maglio. On distinguishing epistemic from pragmatic action. *Cognitive Science*, 18, 1994, 513–549.