Generating an Artificial Nest Building Pufferfish in a Cellular Automaton Through Behavior Decomposition

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DOI: 10.4018/IJAIML.2019010101

ABSTRACT

A species of pufferfish builds fascinating circular nests on the sea floor to attract mates. This project simulates the nest building behavior in a cellular automaton using the morphognosis model. The model features hierarchical spatial and temporal contexts that output motor responses from sensory inputs. By considering the biological neural network of the pufferfish as a black box, and decomposing only its external behavior, an artificial counterpart can be generated. In this way a complex biological system producing a behavior can be filtered into a system containing only functions that are essential to reproduce the behavior. The derived system not only has intrinsic value as an artificial entity but also might help to ascertain how the biological system produces the behavior.

KEYWORDS

Artificial Neural Network, Cellular Automaton, Computational Biology, Morphognosis, Pufferfish Nest Building

INTRODUCTION

The purpose of this paper is to describe a system that is capable of translating biological behaviors generated by a brain into artificial behaviors generated by an artificial brain. This system is meant to work on a variety of behaviors generated by organisms. Here a species of pufferfish is selected as a biologically inspired model for its complex nest building behavior. The paper is not intended to offer new or additional findings about pufferfish.

A species of pufferfish, Torquigener albomaculosus, creates an astounding circular nest structure on the sea floor near Japan, as shown in Figure 1. The nest is built by the male for the purpose of attracting a female for mating. The nest contains a central smooth area surrounded by radial furrows and is about 2 meters in diameter. The 12-centimeter-long pufferfish sculpts the furrows by sweeping sediments with its fins as its travels back and forth lengthwise along each furrow. The female lays her eggs in the fine sediments in the central area which are then fertilized by the male (Kawase et al., 2013).

How does a pufferfish, whose brain contains approximately 10 million neurons, instinctively construct such a complex structure? Nature is rife with such interesting animal exploits. Termites build and maintain complex nests by coordinating the efforts of a massive number of individuals
Spiders build complex webs (Murawski, 2004). Birds construct elaborate nests (del Hoyo et al., 1992). Honey bees coordinate foraging through a body language signaling system (von Frisch, 1967). These organisms are all related to humans to some degree. Considering nature’s propensity for extending and repurposing capabilities, unlocking the secrets of animal intelligence is a worthy step toward understanding the underpinnings of human intelligence.

Evolution is a trial-and-error tinkerer that makes extremely complex life forms. Even the well-known tiny nematode worm, C. elegans, with only approximately 1000 cells, 302 of which are neurons, remains a daunting subject for researchers (Wood, 1988). On an even smaller scale, geneticists are beginning to entertain the notion that most traits are the result of contributions from a great deal of the genome (Boyle et al., 2017).

One proposal to extract essential information from nature’s witch’s brew of complexity is the “radical reimplementation” approach (Lehman and Stanley, 2014). The idea is to discover general principles by intentionally diverging from nature in features that might be incidental or artefactual. If the core behavior is preserved after diverging, then the reimplemented features can be excluded from general principles. As an example, consider the case for discovering principles of flight from examination of bird wings. In the biological implementation, flapping wings are universal; yet in the artificial realm, fixed wings are the norm. It is the aerodynamics of wings that is common to both.

In simpler creatures reverse engineering is sometimes feasible. For example, the navigation skills of honey bees are of value to drone technology. Fortunately, it appears that the modular nature of the honey bee brain can be leveraged to replicate this skill (Nott, 2018).

Another approach is to consider a biological system as a black box and decompose its behavior into components that model the behavior in an artificial implementation. The expectation is that the artificial system will be less complex than the biological one, capturing only what is essential to recreate the behavior, and possibly more amenable to analysis. For artificial intelligence, which is more concerned with function over form, this can be an end in itself. Yet even for biologists, the artificial system may offer hints as to how the biological system performs.

An example of this approach addresses a need to distinguish mutant strains of C. elegans nematode worms based on movement variations (Li et al., 2017). An artificial neural network (ANN) was trained to closely emulate recorded worm trajectories. Although the network was not directly trained to perform classification, neuron responses within the network were found to perform well as mutant strain classifiers.
Games, Supply Chains, and Automatic Strategy Discovery Using Evolutionary Computation
T. Gosling (2007). *Handbook of Research on Nature-Inspired Computing for Economics and Management* (pp. 572-588).
[www.igi-global.com/chapter/games-supply-chains-automatic-strategy/21153?camid=4v1a](www.igi-global.com/chapter/games-supply-chains-automatic-strategy/21153?camid=4v1a)

A Multiscale Computational Model of Chemotactic Axon Guidance
Giacomo Aletti, Paola Causin, Giovanni Naldi and Matteo Semplice (2011). *Handbook of Research on Computational and Systems Biology: Interdisciplinary Applications* (pp. 628-645).
[www.igi-global.com/chapter/multiscale-computational-model-chemotactic-axon/52336?camid=4v1a](www.igi-global.com/chapter/multiscale-computational-model-chemotactic-axon/52336?camid=4v1a)