Evolving Genetic Regulatory Networks for Online Neurogenesis

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Abstract

We evolve a Genetic Regulatory Network (GRN) in a three dimensional morphogen gradient environment to determine the topology of the neurons in a Spiking Neural Network (SNN). A genetic algorithm is used to optimize the GRN, selecting individuals based on the performance of the SNN grown by the GRN. Performance is measured on two tasks: visual discrimination and robotic foraging. Early results show potential for this method as both an indirect encoding and online regulator of neural networks.

Introduction

Artificial neurogenesis has been a fascination of the artificial life community long before the advent of modern neural networks. Gruau (1994) evolved grammars which encoded ANNs capable of controlling six-legged robots. Fleischer and Barr (1994) used controlled morphogen emissions to guide the growth of complex neural network morphologies. More recently, Kowaliw et al. (2014) covered a number of approaches, such as Wróbel et al. (2012), which showed that GRNs can encode SNNs that exhibit desirable and realistic spiking patterns.

In this abstract, we provide an overview of an artificial neurogenesis model designed to both growth and continuously modify an online SNN. The design and evaluation of this model is undergoing; we present a broad overview in 2 and preliminary results in 3.

Neural model

Neurons are modeled as single points p in a three dimensional cube with an orientation o. They emit morphogens and can move in the space following mophogen gradients, aligning both their orientation and movement with the chosen gradient and bound in all dimensions. Morphogens are distributed radially from each neuron's emission, e_m and are normalized globally, the concentration of morphogen m at neuron i computed as

$$c_{m,i} = \frac{1}{\max(c_i)} \sum_j \frac{e_{m,j}}{\parallel p_j - p_i \parallel} \quad (1)$$

At each time step, morphogen concentrations are recalculated based on the emissions from each neuron, which in turn are determined by the neural controller. At each interval of time steps t_{action}, neurons take one of the following actions: movement, division, quiescence, and, for hidden neurons only, apoptosis. The neuron's β parameter, used to determine its firing influence, is also updated at each t_{action}.

Neuron controller: GRN

The neuron controller in this model is a genetic regulatory network. In nature, a GRN is a network of proteins that controls the behavior of cell. An explanation of GRNs, and specifically the model used in this work, can be found in Cussat-Blanc and Banzhaf (2015).

The inputs to the GRN are an important consideration in the design of the model. The following inputs have been chosen not only to enable the growth of interdependent neurons, but also to give each individual neuron information about its contribution to the performance of the network. The inputs are the neuron position p, the morphogen concentrations at p, neurotransmitter concentration, firing decay, problem reward, and the neural influence coefficient β.

The reward is specific to the problem domain, as explained in 3. Firing decay is an exponential timer reset every time a spike is fired in the neuron, to give the controller input as to how recently the neuron fired. There are three position inputs, one for each dimension, and five morphogen inputs, one for each morphogen emitted by other hidden neurons, and two for the distinct input and output morphogens.

The controller's outputs then determine the state and actions of each neuron. The outputs consist of actions: movement along a morphogen gradient, division, apoptosis, and quiescence. Also output are the morphogen emissions e_m, θ_e, δ_β, and θ_{δ_β}. Morphogens are emitted from the neuron and β is updating according to

$$e_m = \frac{e_m - \theta_e}{e_m + \theta_e} \quad \text{and} \quad \beta_{t+1} = \beta_t + \frac{\delta_\beta - \theta_{\delta_\beta}}{\delta_\beta + \theta_{\delta_\beta}} \quad (2)$$

An action is chosen as the maximum output from the action outputs. If one of the 5 movement actions are chosen, the

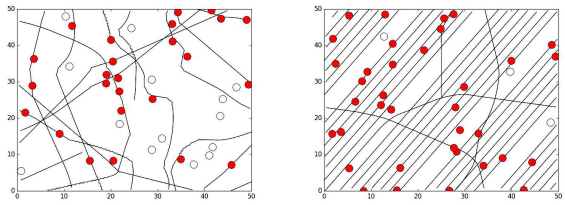

Figure 1: The path and food consumption of the robot. Consumed food is filled; ignored food is empty. The first path displays a use of sensors, the other displays an ignorance of them.

neuron orients based on the chosen morphogen gradient and moves along it.

Firing model

The neurons are then translated into a leaky integrate and fire spiking neural network, with position in the cube determining neural connectivity. The weight from a neuron i to another neuron j is

$$w_{i,j} = \frac{1}{\exp\left(\beta_i \frac{o_i \cdot (p_j - p_i)}{\|o_i\|}\right) - 1} \tag{3}$$

where the distance between the neurons is the projection of their distance vector onto the orientation of i, o_i. Input neurons are oriented along the z axis, facing the output neurons directly. Neurons fire if the neurotransmitter concentration reaches the threshold vt, at which point the neurotransmitter concentration is set to resting potential, vr; otherwise they leak a percentage α of their neurotransmitter at each timestep.

Evaluation

GRNs were evolved in a genetic algorithm based on Cussat-Blanc et al. (2015), using a robotic foraging task for fitness. In this task, a two wheeled robot is placed in a torus environment populated by food particles. The robot has 8 sensors on its front half. The robot turns and moves by firing neurons on the left and right side of the output plane, accelerating the left and right wheel, respectively. Eating prolongs the robot's life, which is decreased at each time step. The problem ends when the robot runs out of life, and fitness is awarded based on the amount of food consumed. The reward input provided to the GRN is the current life of the robot. A growing ANN forages over five instances of a map generated at the beginning of each evolutionary generation and the worst fitness is chosen, which motivates improvement and stability of the ANN.

Using an evolved GRN and the resultant ANN, the robot displays a tendency to move towards food detected by select sensors; the topology may underutilize some inputs, evident as food not being approached from certain angles. Another undesirable evolutionary trait is the efficient blind search methods that attempt to cover the entire map, ignoring food placement. As seen above, a persistent movement strategy though the map can result in food consumption competitive with the strategy of following sensory input.

The model acheieved near perfect fitness on the foraging problem using both sensor following and map coverage strategies. The stability of the network is still under consideration; while the model grows and modifies the network according to the reinforcement problem, as desired, the modifications can also destabalize the network. We are focused on addressing this issue in the continuing development of the model.

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