BEST BRAINS? Neurocontroller evolution in Dynamic versus Static Environments

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INTRODUCTION

Which brains are best? Previous research suggests that brains evolve with respect to the environment in which an organism interacts, and that brains with distinct modules provide an evolutionary advantage within a changing environment compared to more integrated structures (Clune et al., 2013 and Livingston et al., 2016). Do these claims hold true for traditional and non-traditional neural nets?

Presently, we aim to examine this claim by comparing the evolution of a simulated robot's neuro-controller in a static and a dynamic environment using both traditional artificial neural networks (ANNs), and weight agnostic neural networks (WANNs).

MODELING APPROACH

Our model features **GridBot**, a simulated 1x1 robot that can traverse a GridWorld (intended to emulate a terrestrial robot). GridBot features **5 sensors**: a right infrared sensor (IR), a left IR, a right light dependent resistor (LDR), a left LDR, and a front bumper. Based on the input of these sensors, GridBot can make the following **4 moves**: turning clockwise, turning counter-clockwise, stepping forward into a new square (if there is no obstacle), and stepping backward.

In the **static condition**, GridBot traverses a 10x10 matrix with a border, 5 obstacle blocks congregated in the center, and a light source at the top of the grid. In the **dynamic condition**, GridBot traverses an NxN matrix (totaling of 100 squares) with 5 obstacle blocks and one light source randomly placed. GridBot's fitness is determined by the amount of light it collects within a trial (100 moves).

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10
1	1	1	1	1	1	1	1	1	1	1
2	1	NA	NA	NA	NA	NA	NA	NA	NA	1
3	1	NA	NA	NA	NA	NA	NA	NA	NA	1
4	1	NA	NA	NA	1	NA	NA	NA	NA	1
5	1	NA	NA	1	1	1	NA	NA	NA	1
6	1	NA	NA	NA	1	NA	NA	NA	NA	1
7	1	NA	NA	NA	NA	NA	NA	NA	NA	1
8	1	NA	NA	NA	NA	NA	NA	NA	NA	1
9	1	NA	NA	NA	0	NA	NA	NA	NA	1
10	1	1	1	1	1	1	1	1	1	1

Figure 1. Static Condition Gridworld

BOT SPECIFICATIONS

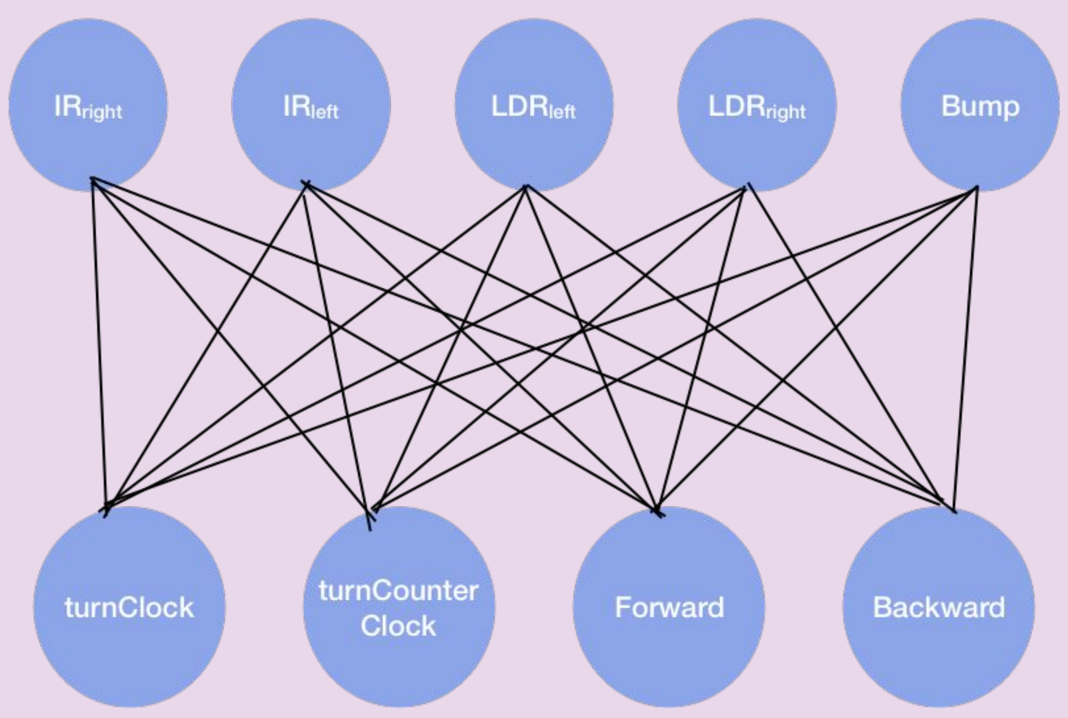

Figure 2. ANN Setup

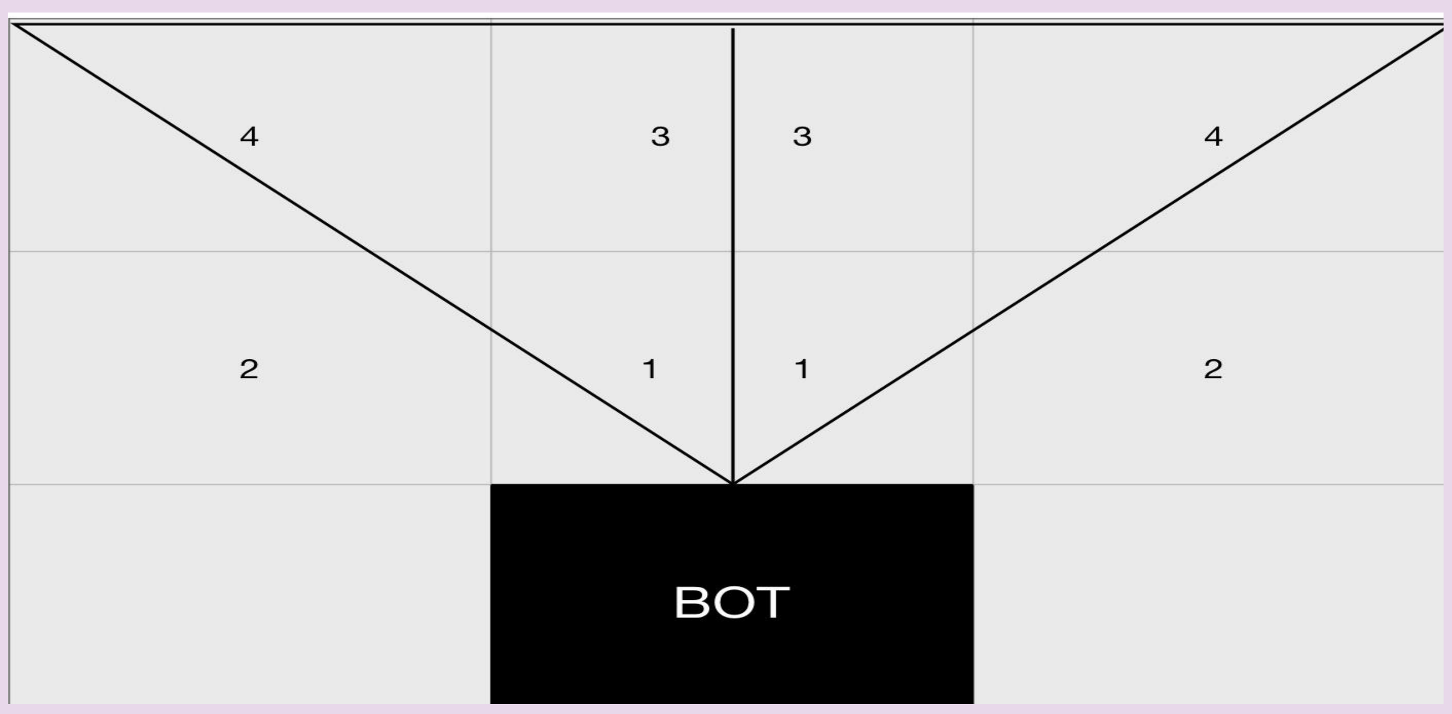

Figure 3. IRs. GridBot searches for an obstacle in squares 1 through 4 in order, and if an object is found in any space, the IR value becomes the distance between that square and GridBot's position

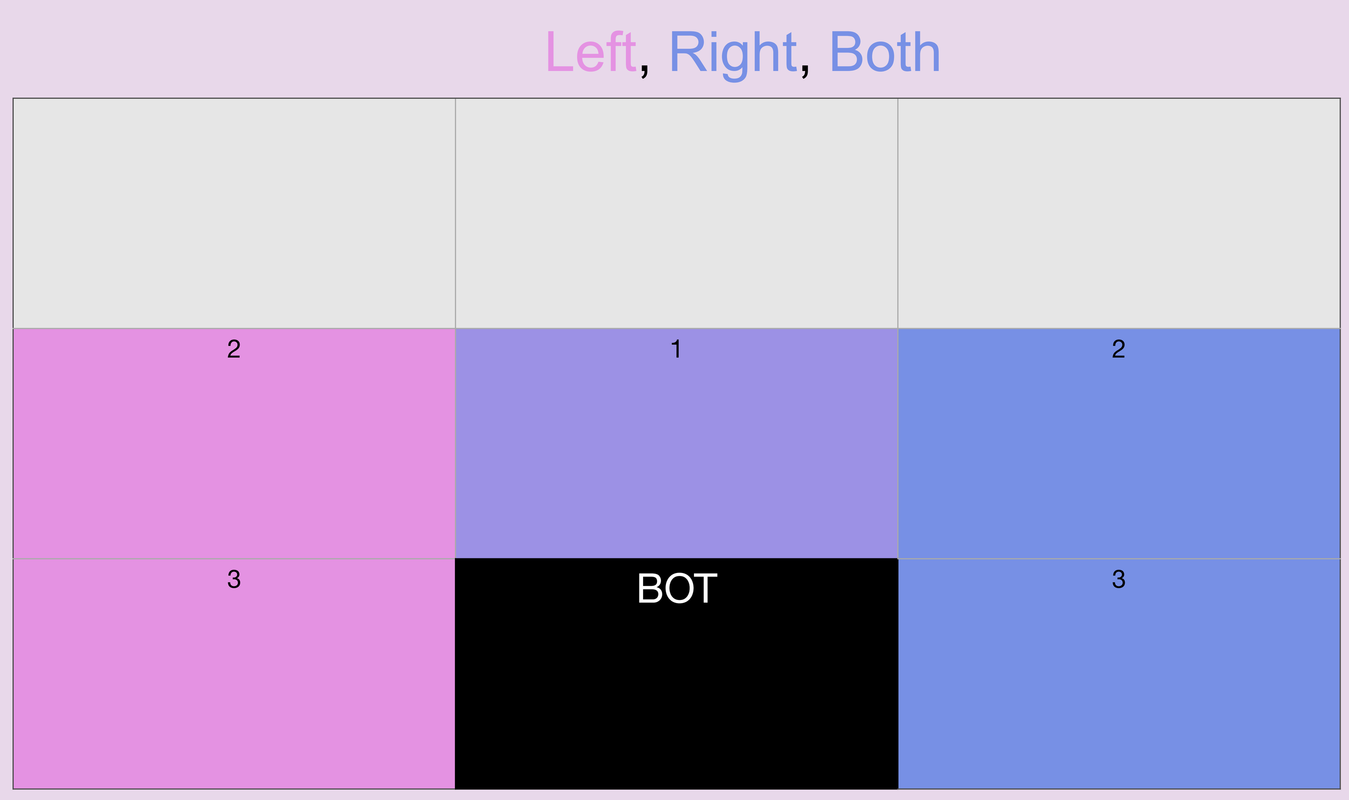

Figure 4. LDRs. GridBot's left and right sensors each take the average of 4 squares every move: the square GridBot is in, plus the 3 adjacent squares.

PROGRESS REPORT

Currently, GridBot's sensors, motors, and ANN have been implemented, and static GridWorld has been created. A move function has been implemented that creates the ANN and decides moves based on sensor input. There are minor bugs currently preventing a full trial of GridBot that will hopefully be resolved imminently, and dynamic GridWorld will only require minor tweaks.

Next steps will include implementing the evolutionary algorithm for the ANN GridBot trials. This algorithm will take the most fit GridBot within the generation (10 bots)'s ANN and clone it, and will populate 8 bots of the new generation with the top 3 performers' ANN from the previous generation proportionally based on relative fitness, and also add a new bot with a randomly weighted ANN. Phase 2 of this project will transition into a Senior Thesis, and involve implementing WANNs using NEAT (Stanley and Miikkulainen, 2002).

REFERENCES

Clune, J., Mouret, J. B., & Lipson, H. (2013). Summary of the evolutionary origins of modularity. *GECCO 2013 - Proceedings of the 2013 Genetic and Evolutionary Computation Conference Companion*, 23. https://doi.org/10.1145/2464576.2464596

Livingston, N., Bernatskiy, A., Livingston, K., Smith, M. L., Schwarz, J., Bongard, J. C., … Long, J. H. (2016). Modularity and sparsity: Evolution of neural net controllers in physically embodied robots. *Frontiers Robotics AI*, *3*(DEC), 1–16. https://doi.org/10.3389/frobt.2016.00075

Stanley, K. O., & Miikkulainen, R. (2002). Evolving neural networks through augmenting topologies. *Evolutionary Computation*, *10*(2), 99–127. https://doi.org/10.1162/106365602320169811, http://www.cs.ucf.edu/~kstanley/neat.html