Multi-Robot System Evolution with a Cost of Neural Complexity

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ABSTRACT

This paper seeks to shed some light on the conflicting theories regarding the role that complexity plays in the evolution of robot morphologies. Specifically, it looks to contrast the results on imposing a cost of complexity during evolution versus evolution without a cost on complexity. This paper will additionally be focusing on the *neural* interpretation of the definition of morphological complexity. During this research, it has been defined as the number of nodes and links, in the connected digraph, that represents the artificial neural networks which act as the controller of a robot body. The design of this research made use of an extended version of a robot simulator which ran numerous experiments (with varying parameters) on simulated robot bodies, as has been done in previous research. These results were statistically verified and analysed using normal distribution and hypothesis testing, thereby coming to the following conclusion: imposing a neural cost on complexity resulted in an increased selection pressure towards producing simpler robot morphologies while failing to derive behaviour that was at least as effective as those that evolved without a cost.

1 INTRODUCTION

Evolutionary robotics has grown increasingly popular in the last 3 decades, recently focusing attention on the subfield of Collective Robotics, specifically researching evolutionary complexity costs and their associated effect on collective robot task performance. The reasons for this research are rooted in the practical benefits in developing low-complexity, and therefore low-cost, robot controllers for real-world production and use all while reducing computation time [3]. More importantly, this form of simulation provides insights into theories and concepts that form the basis of this research, that is to investigate the previously inaccessible questions in evolutionary and biological theory, such as the nature and origin of complexity [6].

In biology, there are hypotheses which suggest that neural complexity in living organisms is a function of social and cooperative behaviour [6]. It is difficult to facilitate the study of these hypotheses as the resources required are often not feasible in the physical world. Therefore, the idea of simulating collaborative tasks in environments with evolving agents has grown in popularity. Simulations can be run at a higher magnitude and in a fraction of the time it would take to use physical variables.

In evolutionary robotics, resources are limited and the complexity of a robot body can result in a significant computational overhead when task complexity becomes necessarily large. Robot configurations and evolutionary algorithms are constantly in pursuit of optimization to ensure task completion in the most effective manner possible [4]. This naturally leads to the motivation for minimizing complexity while maximizing performance. Imposing a cost on complexity should provide the results necessary to make an informed conjecture about the legitimacy of its effects on collective robotics performance.

A 2008 study by Capi and Kaneko [3] investigated the multi-objective neuroevolution of low-complexity neural controllers for robots required to perform multiple, simultaneous tasks. The takeaway was that neural controllers could be evolved to achieve effective task performance while maintaining a simple morphology. Furman, Nagar and Nitschke [13] recently researched the impact of a morphological complexity cost on task performance. In this study, single- and multi-objective neuroevolution strategies were compared. The single-objective neuroevolution simulations, using Neuro-Evolution of Augmenting Topologies-Morphologies (NEAT-M) [9], aimed to maximise task performance without any consideration for complexity, NEAT-M-MODS multi-objective behavior-morphology evolution method extension of NEAT-M [13] was tasked with the additional constraint of minimising morphological complexity. The results show that both approaches produced robots that performed equally in simple environments, however, as task difficulty increased those robots that were evolved with a complexity cost performed higher than those that were not, all while maintaining a simpler morphology. This is in contrast to previous research [1].

Both of these papers are inconsistent with results obtained from Auerbach and Bongard [1] who found that an imposed complexity cost on morphology paired with increasingly complex environments resulted in increased robot complexity. The stance of this research is based on the assumption that a multi-objective optimisation of performance and complexity is neither biologically plausible nor is it representative of natural collective behaviour systems where neuro-evolution is constrained by energy restrictions. Therefore the goal of this research paper is:

> *We aim to broaden the available research and information regarding the intriguing relationship between evolutionary processes and complexity (morphology), specifically their connection to collective robotics teams cooperating to achieve task gathering and how that relationship derives performance (behaviour). This will be done by looking at particular interpretations and definitions of these concepts.*

1.1 1.1 Hypotheses:

We have derived the following hypotheses:

- ***H0***: Imposing an evolutionary fitness cost on neural complexity results in collective robots that are less complex but do not display efficient behaviour in increasingly difficult environments when compared to those evolved without a cost.
- ***H1***: Selection pressure for morphological complexity will not increase as task (environment) difficulty grows more complex.

2 BACKGROUND

The following seeks to provide an overview of the topics and areas of research that form the foundation and motivation for this papers' scientific hypothesis and goal.

2.1 2.1 Neuroevolution of Augmenting Topologies (NEAT)

Neuro-evolution (NE) [**?**] is the intersection of two prominent areas of Machine Learning, Evolutionary Algorithms (EA) [22] and Artificial Neural Networks (ANNs) [26]. EAs are used to iteratively build and evolve ANNs in a process that is inspired by the principles of Darwinian evolution [**?**]. One advantage of this pairing is that it allows for fairly generic ANNs separated only by their fitness function, to be evolved to complexity, efficacy and efficiency from an ANN node [16, 19].

NEAT [20] is a neuro-evolutionary algorithm that uses reinforcement learning to optimise and converge the structure of increasingly complex ANNs. Network topologies are encoded in genomes describing their neurons and connections. NEAT explicitly aims to evolve complexity by directly evolving the architecture and weights of a network.

NEAT is built upon the following three principles:

(1) *Historical marking:*
A part of the connection genome that stores information regarding the ancestral history of the gene and is assigned an *innovation number*. This allows for a coherent crossover between the genomes of parents and solves the issue of *competing conventions*.
(2) *Speciation:*
Allows new structures introduced into the network via topological innovation the chance to mature before premature elimination from the population. Speciation occurs via dissimilarity amongst groups and allows members of a species to optimise in their species before doing so with a larger population.
(3) *Complexification:*
This ensures that the complexity of ANNs starts low and increases incrementally over time to converge towards a solution.

Overall, the advantages of NEAT and Neuroevolution include: the lack of a need for labeled training data [8]; an unmatched complexity and necessary abstraction allowing for the discovery of *sophisticated* behaviours [19]; and novelty from randomness, leading to the discovery of *unique* and *innovative* behaviours [16]. These properties lend well to attempting to capture and simulate the real phenomena and optimisation that lead to the evolution of life.

2.2 2.2 Evolutionary Robotics (ER)

Evolutionary Robotics (ER) is the simulation of artificial robot agents to be used in scientific research and experiments to study and better understand the behaviours of natural organisms. Often these robots are modelled after some neural structure that is an abstraction of biological neural networks. This allows researchers the opportunity to study phenomena and behaviour that is often not possible or feasible to observe in the real world simply due to resource constraints and evolutionary requirements.

There are three key focuses of ER: *Controller evolution*, which aims only to artificially design and evolve the neural controller of a robot, while the morphological structure remains fixed; *Morphology evolution*, which conversely evolves the morphology or substrate of a robot; and *Simultaneous Evolution of Controller and Morphology*, which naturally is the combination of the two preceding approaches.

There has been a lot of focus of ER on *collective robotics* and *collective gathering tasks*, where agents are required to work cooperatively to solve some problem. Collective robotics systems are abstractions of natural communities of organisms displaying a multitude of evolutionary paths across ecological niches [4], as such this area of research has been used to address questions regarding the evolution of robot complexity and specifically under what conditions that evolution occurs.

A paper by Duarte et al. [5], investigated a swarm robotics system with evolved control operation in a real-world uncontrolled environment using NEAT. Robot controllers were evolved to perform four common collective tasks: *Homing*, a sequential navigation to way-points while avoiding obstacles; *Clustering*, which places robots nearby one another in a confined space; *Dispersion*, requiring robots to maintain a predefined distance from their nearest neighbour; and *Area monitoring*, which requires robot coordination to cover as much ground of a geo-fenced area of interest as possible. They showed that simple evolved behaviours can be combined to complete a team mission. Their research was fairly unique in that it experimented with both simulated and real robots. The results demonstrated that evolutionary robotics techniques are a viable approach for controlling multi-robot systems in real-world scenarios.

Watson and Nitschke [25], researched the effectiveness of various adaptive morphology methods applied to evoke collection behaviours in a robot team. They employed collective gathering tasks that required cooperative behaviour from the robots to push the collection of blocks in an environment, such that the blocks were connecting and different blocks required varying degrees of cooperation. A robots goal was to have all blocks connect in its lifetime. Their goal was to determine if the robot controllers that were evolved were robust to different morphologies. Controllers were generated using a *Compositional Pattern Producing Network* (CPPN) and controllers and morphologies were evolved using *Hypercube-based Neuro-Evolution of Augmented Topologies* (HyperNEAT). A later paper by Putter and Nitschke [15] researched similar objectives, both papers showed that HyperNEAT's indirect encoding

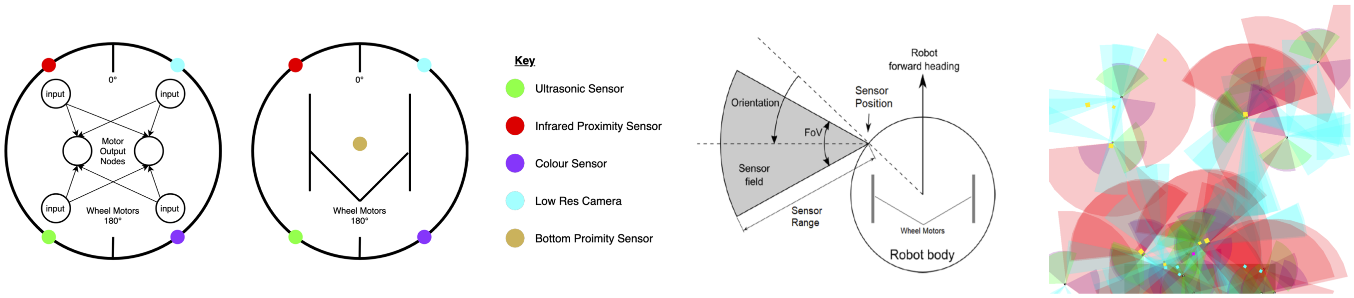

Figure 1: *Left*: Visual representation of the Khepera-III [12] robot that the robots' morphology has been modelled after. *Middle left*: Key containing the descriptions of each sensor that can be used by a robot controller. *Middle right*: A diagram representing the simulated robot model, it depicts the field-of-view of the various sensors described previously. Each robot body is controlled by an Artificial Neural Network that maps to the input (sensors) and output (actuator) nodes. *Right*: A snapshot of the simulator [13] containing a population of robot controllers actively attempting to coordinate as many blocks in the target area as possible. The colours relate to the field-of-view for the previously described sensors. Figure taken from [13]

for evolving controllers in homogeneous robot teams was very effective. Evolved controllers were robust to morphological change, in contrast to those with a fixed morphology. This demonstrates the effectiveness of simultaneous controller and morphology evolution when compared to only controller evolution. This is highly advantageous to the rapid design and construction of robots in the real world, where resources are limited. Simpler controllers can be evolved with similar performance to more complex ones.

In a 2006 paper by Eiben, Nitschke and Schut [7], a collective specialization method was created to produce multi-robot system controllers that outperformed conventional NE methods. Robots were required to explore unknown environments for features of interest, or *red rocks*, given strict time and energy constraints. Energy usage was constrained in the form of a reward system, a robot would venture out in search of *red rocks* and after it had evaluated them, it was eligible for a fitness and energy award. When a robots' energy dropped below a certain amount it returned to base and was awarded energy based on its total *red rock* value. *Collective Neuroevoltion* (CONE) was used to pair up and produce child genotypes from random pairs of a percentage of the fittest genotypes.

2.3 2.3 Robot Complexity

This refers to the state of the intricacy of a robot controller. There are two diverging definitions for what constitutes this metric: *morphological* and *neural complexity*.

Morphological complexity is linked to the physical representation of a robot body, which is a calculation that includes its shape as well as its quantity and arrangement of sensors [1]. A formula defined by Furman, Nagar and Nitschke [13] that takes the number of sensors (n) on a controller as well as the field of view (f_i) and range value (r_i) for each of the sensors was expressed as follows:

$$M = 5 \times \sum_{i=1}^{n} \left(\frac{f_i - \wedge F_i}{\vee F_i - \wedge F_i} + \frac{r_i - \wedge R_i}{\vee R_i - \wedge R_i} \right) \tag{1}$$

Where $\vee F_i$ and $\wedge F_i$, and $\vee R_i$ and $\wedge R_i$, are the maximum and minimum possible values of f_i and r_i, respectively.

Neural complexity is linked directly to the structure of a controllers encoded ANN and is a calculation of the magnitude of the network. Capi and Kaneko [3] developed a definition for neural complexity (N) as the number input nodes nr_i and hidden nodes nr_h in the ANN of a controller. This is expressed as the following:

$$N = nr_i + nr_h \tag{2}$$

This paper will extend the definition of *neural complexity* as described by [3], this method is detailed in section 3.1 of this paper. In doing so, the goal of this paper is to add to previous research, while offering a different interpretation and implementation of neural optimization that is more accurate, biologically speaking than directly enforcing such a cost through multi-objective optimization.

2.4 2.4 Single-Objective Optimisation with a Cost of Complexity

Single-Objective (SO) NEAT-M refers to a neuro-evolutionary algorithm that aims to maximise effective robot behaviour (task performance), the inclusion of the complexity cost adds the additional selection pressure for simple robot morphologies (controllers). This is has been the topic of numerous papers. As mentioned previously, the research conducted by [13] implemented a similar idea, however, their method opted to employ a Multi-Objective (MO) NEAT-M approach, where not only was task performance maximised, but robot complexity was additionally minimised- or in other words, morphological simplicity was maximised. This intuitively resulted in the desired effect.

This research was motivated by the findings of another paper by [9] which laid the groundwork by extending and comparing NEAT with an alternative algorithm NEAT-M that was later used future research. This particular paper concluded that the lack of imposing any form of the morphological cost was the cause of selection for increasingly complex controllers as environment difficulty increased. The continuation of this notion is what has lead to the motivation for this paper.

Given these papers as a background, this research is interested in the hypothesis that imposing a cost may have some effect on evolving effective behaviours, however, we conjecture that a mathematical approach (MO) is far too artificial to be concluding biological plausibility. Instead, we seek to investigate an alternative method for constraining energy expenditure, we follow the formula and definition introduced in section 2.3 and further expanded on in section 3.1. The cost will be interpreted neurally and more importantly, it will be treated as a time-step *reduction* rather than an *algorithmic objective*. In this way we are effectively simulating the notion of a battery for the robot controllers, this is more representative of natural collective behaviour systems- where neuro-evolution is similarly constrained by energy demands.

3 METHODS

This study evaluates a single-objective (maximise task performance) NEAT-M [9], versus the same algorithm with the addition of an incurred complexity cost for co-adapting, homogeneous robot controllers in various collective gathering task environments.

3.1 3.1 neural Complexity

In Neuroscience, a brain is typically represented by a graph $G = (V, E)$, where V is the set of nodes (neurons) of the brain and E is the set of connections between two brain regions [11, 21]. This paper proposes that neural complexity be the sum of the number of input and hidden nodes in a network as well as the connections between them. This can be expressed by the following:

$$N = v + e \tag{3}$$

Where v is the number of nodes in the set V, e is the number of connections in the set E and $G = (V, E)$ is the graph that represents the ANN of a robot controller.

3.2 3.2 NEAT-M

NEAT-M [9] extends NEAT by evolving a direct genotypic encoding of both robot behavior and morphology [13]. That is, it introduces the idea of associating the input layer of an ANN with the sensors on the corresponding robot body. These sensors are seen as additional genes, namely: *type*, *bearing*, *orientation*, *field-of-view* (FOV) and *range*. In order to accommodate for the evolution of these additional genes, the following genetic operators were added: *sensor position*, *sensor number* and *sensor FOV and range*. The functionality of these operators include adjusting sensor parameters and removing a sensor entirely from the robot body [9].

3.3 3.3 NEAT-M with a neural Cost

This method retains the algorithmic functionality of NEAT, but it introduces the neuro-evolution cost on complexity into the simulation. At the start of each generation, all robots in the homogeneous population are given a battery that has an exhaustive limit, for each time-step (i.e. robot moves one unit in any direction) the complexity of the ANN controlling a given robot is deducted from the robot's battery. A simulation task trial will end when the robots'run out of battery.

For both methods, the evolutionary algorithm is given by the following pseudocode (adapted from [9]:

- N (Figure 4) genotypes are randomly created with two motor outputs and one bias node connected. All controllers are initialized with five sensory input nodes. All sensory input nodes are fully connected to motor output nodes and connection weights are randomly initialized to within a given range (Figure 4).
- Genotypes are ranked by fitness, they are randomly selected from the genotype population's elite portion and copied M (Figure 4) times as the M controllers make up a robot team. The genotype is decoded into a morphology that is copied to each of the M robots in simulation. For controllers with a cost, genotypes are additionally initialized with a battery capacity (Figure 4) and an associated neural energy cost (see section 3.1).
- For each generation, a genotype is evaluated Q times after which an average fitness is then assigned to the genotype (entire team) being evaluated. A simulation task trial will end when the robots' run out of battery.
- One generation is the evaluation of all N genotypes. Speciation and genetic operators are applied at the end of each generation within the population's elite portion and a new population generated.
- A new population takes the place of the previous one and steps 24 are iterated for X (Figure 4) generations.

	Number of Blocks of Size:		
	Small	Medium	Large
Environment 1	10	5	0
Environment 2	5	5	5
Environment 3	0	5	10

Figure 2: Number of block of each size in each experiment, where Environments 1-3 correspond to level of difficulty, i.e. Simple, Medium and Difficult.

			Environments		
Experiment Set ID	**Objective**	**Cost**	1	2	3
SO	T	None	SO1	SO2	SO3
SOC	T	N	SOC1	SOC2	SOC3

Figure 3: SO refers to single-objective (maximize task performance *T*) NEAT-M, while SOC refers to single-objective NEAT-M with a neural cost *N*. Each experiment set is repeated 14 times.

4 EXPERIMENTAL SETUP

There are two sets of three experiments, where each experiment corresponds to an increasing level of difficulty detailed in (Figure 5). In each experiment, robots are required to collectively gather blocks of different sizes in a designated zone. In doing so, their controller-morphologies are evolved for maximum task performance. The first set of experiments employs the standard NEAT-M method, only maximizing task performance, while the second set introduces the neuro-cost function in addition to the performance objective. Each experiment set is run twelve times, where an average of task performance and neural complexity is taken over all runs. These

Neuro-Evolution Parameters	
Generations per experiment	250
Trial evaluations per phenotype	5
Population size	150
ANN connection weight range	[-1.0,1.0]
Sensor mutation	0.08
Add sensor mutation	0.07
Sensor FOV / Range / Bearing / Orientation Perturb	Caunchy mutation (0, 5)
Connection weight mutation probability	0.335
Initial connection density	0.5
Initial sensory input nodes / Output nodes	5/2
Output nodes	2
Crossover / Mutation	0.32/0.34
Simulation Parameters	
Timesteps per simulated trial evaluation	10000
Battery size	100000
Robot team size	20
Robot size (diameter) / Gripping distance	0.004 / 0.002 (Portion of environment size)
Maximum robot movement per timestep	0.013 (Portion of environment size moved per iteration)
Initial robot / block positions	Random (Outside gathering zone)
Environment width x height / Gathering zone size	1.0 x 1.0 / 0.5 x 0.5
Small / Medium / Large block size (Width / Height)	0.001 x 0.001 / 0.015 x 0.015 / 0.02 x 0.02
Ultrasonic sensor range / FOV	(0.0, 1.0] / (0.0, π)
Infrared proximity range / FOV	(0.0, 0.4] / ($\pi/6, 5\pi/6$)
Colour sensor range / FOV	(0.0, 0.4] / ($\pi/6, 5\pi/6$)
Low res camera range / FOV	(0.0, 0.8] / ($\pi/9, 8\pi/9$)
Bottom proximity	Downward-facing
Sensory bearing range	[-π, π] *Radians*
Sensory orientation range	[-$\pi/2, \pi/2$] *Radians*

Figure 4: Neuro-Evolution and Simulation Parameters, adapted from [13] with modifications including the addition of a robot *battery* parameter and an adjusted *small block size* parameters

experiments are constructed in a multi-robot collective gathering simulator [9, 13].

4.1 4.1 Simulated Robot Configuration

Each robot is controlled by an ANN that is mapped to the morphological composition of its body, that is the number and arrangement of sensors on its circular base. A robots' morphology is modeled after the *Khepera III* [12] robot, as was done in all previous work [9, 13, 25]. The sensors map directly to the input nodes for the network, they provide environmental feedback that instructs the controller on how to behave, this is illustrated in Figure 1. Morphologies begin randomly and are automatically adjusted and evolved according to performance in the gathering tasks. The simulator used in these experiments is based on the extension produced by Nagar, Nitschke and Furman [13], where the sensory model was extended to include an *Ultrasonic Sensor* and a *Low-Resolution Camera.* Robot configuration has been further extended in this research to include a battery, corresponding to energy level and calculated energy expenditure for each time step as outlined in section 3.1. There is a full detailed report of all configurations and variables in Figure 4.

4.2 4.2 Environment Configurations

The environment in which the robots must cooperate is represented by a two-dimensional plane, wherein they are required to push blocks of varying sizes into a designated gathering zone. Block sizes directly correlate to the level of cooperation required to move them, that is bigger or heavier blocks require more than one robot to push, this is done to simulate a range of task difficulty and place emphasis on cooperative behaviour. The gathering zone constitutes a smaller portion of the environment as a whole and a successful run is measured by the number of blocks successfully placed in that zone before either the timer or battery runs out.

4.3 4.3 Fitness Function

The first experiment will maximize task performance, placing selection pressure behaviour, while the second experiment introduces energy expenditure which is defined as the cost mentioned in section 3.1. Each epoch is run 5 times (before all 250 epochs are repeated 14 times), after which an average of task performance is taken, which defined as the average of team performance for a group of robots in a generation and is maximized by the following formula:

$$T = 100 \times \frac{v_c}{v_t} + 20 \times (1.0 - \frac{s_e}{s_t} \quad (4)$$

Where v_c is the total value of resources in the gathering zone, v_t is the total value of all resources in the environment, s_e is the number of simulation timesteps elapsed, and s_t is the number of trial evaluations per individual.

5 RESULTS AND DISCUSSION

The following section provides a detailed review and discussion of the results produced from the two experiments, which are broken down in Figure 6 and described as NEAT-M with a cost (SOC) and NEAT-M without a cost (SO). All results have been graphed and represented by boxplots to showcase the differences between their trends and distributions. Each experiment consisted of three simulator difficulties, simple, medium and difficult, as mentioned in section 4.2. Each difficulty was evolved for 250 epochs, which were additionally repeated a total of 14 times for statistical significance. Morphological complexity and task performance were both normalized to a range between 0 and 1 and all data points used in hypothesis testing were tested and validated for having a normal distribution.

5.1 Validation of Null Hypothesis

Figure 6 (right) shows that robots evolved with a cost seem to exhibit less neural complexity on average when compared to those evolved without a cost. This margin tends to increase with every epoch. Results were normalized and taken from the average neural complexity for each each difficulty across all runs, where a score closer to 0 implies a robot that has fewer nodes or connections in its ANN (less complex) and a score closer to 1 implies one that has more nodes or connections in its ANN (more complex). Figure 5 (right) details the spread of neural complexity for the best (task performance) networks from each run across all difficulties for both SO and SOC, intuitively we can see that robots evolved with a cost appear to be less complex, which is evident by the far smaller range and maximum value present for each distribution.

In order to confirm this difference, a statistical approach is required. Taking the neural complexity of each of the best performing networks from each difficulty, an F-test [2] (analysis of variance) was performed on each corresponding set of environment difficulties for SO and SOC. This test revealed that the variance between each simple, medium and difficult set was unequal (p-value > 0.05), using this information a Welch t-test [23] was performed rather than a traditional students t-test, since it is both better suited to and more reliable for testing amongst distributions with unequal variances. A two-sided test for a difference of two means was performed for each environment, the results of which revealed that there is indeed a significant statistical difference (p-value < 0.05) between SO and SOC. In other words, robots evolved with a cost displayed a significantly different neural complexity than those evolved without a cost for increasing levels of task difficulty. An additional set of single-sided t-tests were performed, this time testing if one distribution mean was statistically less than the other. All results are summarised in Figure 7 and confirm that robots evolved in SOC were neurologically simpler than those evolved in SO.

Figure 6 (left) details the trend of average task performance across all 250 epochs for both SO and SOC, a score closer to 1 implies a very effective evolved behaviour while a score closer to 0 implies a poor one. We can see that task performances decreases for each increasing level of difficulty and that performance appears worse for SOC. Figure 5 (left) represents the spread of task performance between SO and SOC, the metric taken for this comparison was the maximum task performance of the best performing network from each run, where results were once again normalized and a score closer to 0 means a worse evolved fitness and a score closer to 1 means a better-evolved fitness. Again, it is evident from the spread of each distribution, that task performance decreases for each increasing level of difficulty and behaviour is less effective for SOC in comparison to SO.

Taking a similar statistical approach as before, the task performance of the best performing networks for each environment were taken to produce corresponding sample sets. F-tests were performed on each set and showed that the variance amongst each set of distributions was again unequal (p-value > 0.05), using these p-values, a two-sided Welch t-test was performed for each environment and revealed that there was indeed a significant difference (p-value < 0.05) amongst the distributions. Further investigation used a set of single-sided t-tests, looking for proof that task performance for SOC was statistically less than that of SO. The results were as expected and showed that robots evolved with a cost displayed a worse task performance than those evolved without a cost, for each environment difficulty. All results are summarised in Figure 8.

These findings contradict previous work [13] stating that imposing a cost would produce simpler robots that were at least as behaviourally effective. The findings are additionally inconsistent with other previous research [1, 24] which showed that increased environmental difficulty resulted in more complex morphologies. Since we have shown that robots evolved in SOC are both less complex and less behaviourally effective than those evolved in SO, we therefore fail to reject the null hypothesis, that is to say that imposing an evolutionary fitness cost on neural complexity results in collective robots that are less complex but do not display efficient behaviour in increasingly difficult environments when compared to those evolved without a cost.

5.2 Validation of Alternative Hypothesis

Since we have failed to reject the null hypothesis, it is necessary to understand why we cannot accept the alternative. Looking only at the results of a two-sided t-test, it would have been difficult to say for certain whether *H0* or *H1* was more likely as it would only tell us that the distributions were significantly different from one another but not which was greater or smaller on average. Intuitively, we could have taken this combined with the average trends found in Figure 6 as the conclusive indication that the alternative was not true, however, by making additional use of the single-sided t-test we were able to specifically test for the case that complexity was simpler for SOC and in doing so we can say with a reasonable amount of certainty that the alternative is not true. Selection pressure for morphological complexity did indeed increase as task difficulty grew more complex.

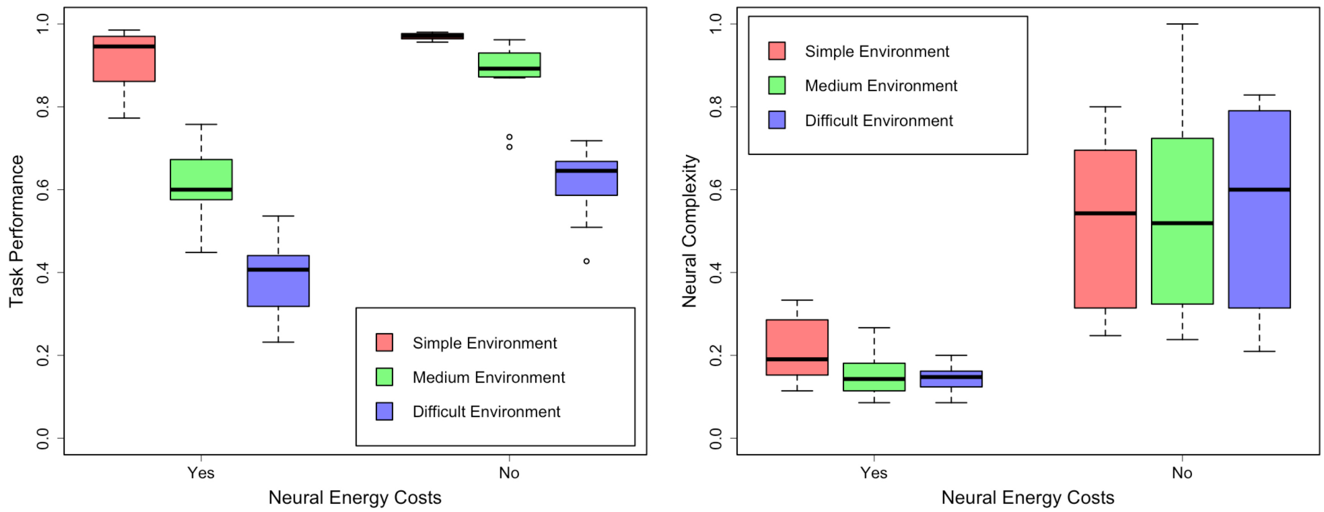

Figure 5: *Left*: Average maximum task performance for the best networks produced by NEAT with and without a cost in the three environments over evolutionary time (generations). *Right*: Average neural complexity for the best networks produced by NEAT with and without a cost in the three environments over evolutionary time (generations)

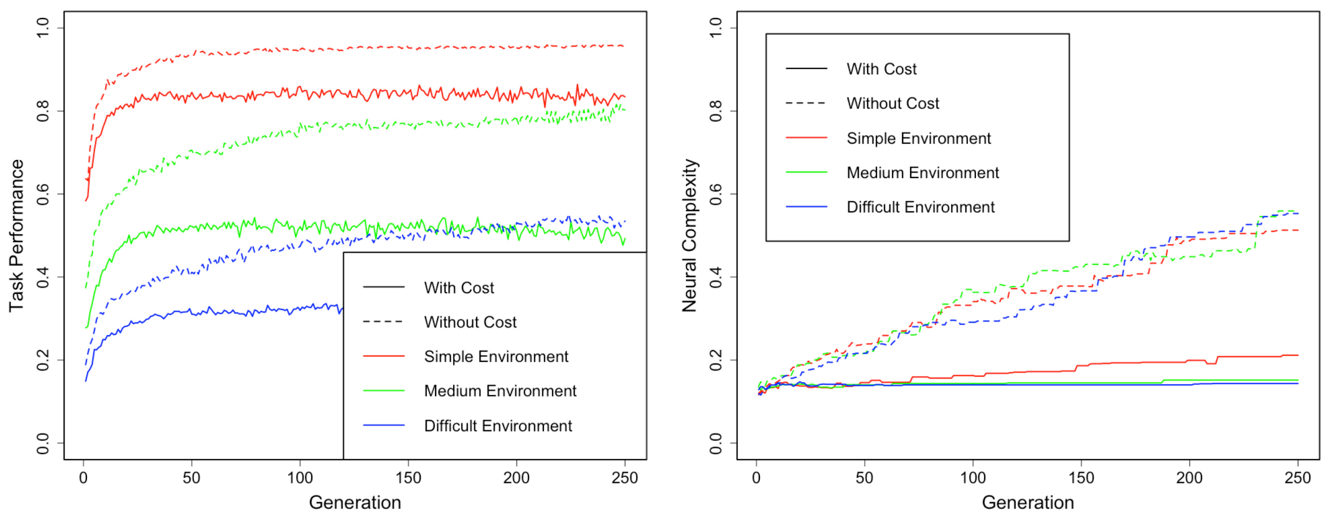

Figure 6: *Left*: Average task performance produced by NEAT over all 14 runs of 250 epochs with and without a cost in the three environments over evolutionary time (generations). *Right*: Average neural complexity produced by NEAT over all 14 runs of 250 epochs with and without a cost in the three environments over evolutionary time (generations)

Neural Complexity	Single-sided	Two-sided
SOC1 vs SO1	<	<
SOC2 vs SO2	<	<
SOC3 vs SO3	<	<

Figure 7: Results from the t-tests performed on each environment set for neural complexity, where entry indicates whether the p-value was less than 0.05.

Task Performance	Single-sided	Two-sided
SOC1 vs SO1	<	<
SOC2 vs SO2	<	<
SOC3 vs SO3	<	<

Figure 8: Results from the t-tests performed on each environment set for task performance, where entry indicates whether the p-value was less than 0.05.

6 CONCLUSIONS

This study evaluated the effects of imposing a cost on neural complexity (the number of nodes and connections in an ANN) for collective robot controllers in a simulated task gathering environment. The experiments measured task performance and neural complexity of robot *behaviour morphology couplings* and evolution occurred over varying degrees of task difficulty. Two sets of experiments were performed, which were designed to contrast the effects of imposing or not imposing a neural cost.

The results showed that imposing a neural cost on complexity resulted in an increased selection pressure towards producing simpler robot morphologies while failing to derive behaviour that was at least as effective as those that evolved without a cost. For each level of difficulty, those controllers evolved with a cost maintained a very low neural complexity, barely increasing at all. Task performance decreased as task environments grew more difficult and performance behaviour was comparably less effective in robots evolved with a cost. This is in contrast to previous work [13], which showed that imposing a cost enabled the evolution of simpler morphologies that retained task performance. The results also contradict other previous research [1, 25], that is that increased environment difficulty results in more complex morphologies. A contradiction was expected due to the intentional differing interpretations for how an energy source should be defined as well as how the expenditure of that energy should be constrained during evolution.

The important takeaway from this research is firstly that introducing energy expenditure as a function of neural complexity that is depleted through a battery is more biologically plausible and in line with natural collective behaviour systems where neuro-evolution is similarly constrained by energy demands. Secondly, it further highlights the importance of how complexity is defined and constrained with regards to its effect on robot morphology evolution, more specifically that there is indeed an intricate and tightly bound relationship between complexity and evolution that could provide for many more interesting insights as the topic of further research and discussion.

6.1 6.1 Summary

The results of this paper were as expected, taking a more naturalistic approach to energy restrictions produced less complex robots that did not perform comparably to or better than those that were not restricted. The experiments conducted and methods of testing applied were effective and produced useful metrics for investigating hypotheses while the definition of morphological complexity used was effective in providing a mechanism for energy consumption.

7 6.2 FUTURE WORK

A useful continuation of this work might include the addition of several more repetitions of each difficulty, at least 20 but possibly more- time and resources provided. Beyond that, the notion of experimenting with different environment or block shapes and sizes might provide an interesting path of research, as did the idea of an alternative interpretation for robot complexity (*morphological* vs *neural* [3, 13]).

Testing different neuro-evolutionary algorithms is another crucial variation, taking the existing environment and simulator configurations from this research and reevaluating them with alternative takes on NEAT, such as HyperNeat. It has been shown that NEAT performs poorly on problems where the optimum of the fitness function changes rapidly between generations. A paper by Krčah [10] produced a novel algorithm, DynNEAT (NeuroEvolution of Augmenting Topologies for Dynamic Fitness Functions), which extends NEAT by changing the size of each species based on its historical performance. The results showed that DynNEAT performs similarly to NEAT for slow or statically moving optimum, but outperforms it on problems with a rapidly moving optimum.

Lastly, there might be an insight to be gained in investigating the combination of both the *morphological* and *nuerological* definition of robot complexity, that is to say, that complexity be interpreted as some union of the controller (ANN) and a robots sensors, or rather a joint usage of physical and cognitive energy.

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