The Cost of Complexity using Single-Objective Evolution

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ABSTRACT

The evolutionary cost of complexity is an interesting topic within biology, robotics and computer science which begs much investigation. This study aims to investigate the impact imposing a cost on complexity will have upon robot evolution, morphology and overall task performance in the context of a collective task-environment. The investigation is taken in a new direction, as the study implements a single-objective solution for imposing complexity costs by proxy of energy costs based on sensor morphology. In addition, this study also investigates the relationships between task performance, environment difficulty and evolved morphology and the impact that imposing a cost of complexity has on these relationships. This is done by using single-objective HyperNEAT-M evolution to evolve robots in a simulated collective-robotics task-environment platform while a draining cost has been imposed upon sensor morphology. Most interestingly is discovered that morphological complexity is naturally higher for robots evolved in simpler task-environments than more difficult ones, when a cost is not imposed upon morphological complexity, however this difference disappears when a cost is imposed upon morphological complexity.

KEYWORDS

Simulation, neural networks, neuro-evolution, collective robotics, evolutionary robotics

1 INTRODUCTION

An ongoing area of much interest and research in both biology[1][16] and evolutionary robotics [9][3] is the questions surrounding the impact differing levels of complex environment has on the complexity of evolved robots. This study aims to take the research in a new direction, and investigate the impact of a cost on complexity on robot bodies, while maintaining the natural evolutionary process, using a simulated evolutionary collective robotics system.

This is particularly interesting in the field of biology, where there has been much research done, and still ongoing, regarding the impact of complexity on evolved individuals. [21][11] Evolutionary Robotics provides an excellent platform to investigate some of these problems, and can provide valuable insight into these deep and meaningful questions.

In addition, the practical use of this study will be in the areas of designing and building real life robots. Often sensors can be costly to both engineer and maintain on a robot in it's environment. Morphologies should be as simple and cheap as possible while maintaining required task performance in task performance.

A collective robotics problem will be utilized, using homogeneous robot teams evolved in a simulator, used in previous works [20] but extended. The population of robots will be co-evolved both morphologically (sensor-motor couplings) and neurologically (behavior-morphology couplings) using single-objective HyperNEAT-M, an extension of classic HyperNEAT [27] [32] evolution that allows for evolution of controllers as well as morphologies, not unlike the extensions put into NEAT-M [13] of the same style.

This work differs from previous work in the area of complexity in robot bodies [3][20] in that we will be using a simulated battery drain technique as a proxy for complexity costs, as opposed to a multi-objective focused approach. This is believed to more accurately represent the standard models of evolution.

Complexity in robot bodies will be defined in this context as a simple function of the number and type of sensors which the robot has, effectively representing a morphological complexity cost. This differs from task-environment complexity, which refers to the inherent complexity of the task environment within which the robots exist. The experiment will be trialed using 3 different sets of increasingly complex task-environments in order to test the effect task-environment complexity has on evolved morphology.

1.1 Research Objective

The research objective is thus broadly to investigate the impact of a cost of complexity simulated on robot bodies through increasingly complex task environments. The specific objectives that run off of this are: to investigate the impact of a cost of complexity simulated on robot bodies with respect to the robot task performance, and to investigate the same with respect to evolved morphology, as well as to evaluate the impact on of increasingly complex task environments on evolved morphology, given a cost of complexity.

Motivations for the formulation of this research objectives stems mainly from ongoing research and previous results which show different results regarding how different forms of morphological complexity evolves as a function of differing tasks and environments [3][20]. Some work was done towards finding out the impact a cost term on evolutionary task performance in order to increase efficiency[24], however this work will differ in that it does not scale the cost as better task performance is reached (as Revello et al. did[24]), as this would not as accurately mimic biological evolution.

2 BACKGROUND

HyperNEAT[27] [32] (Hypercube NeuroEvolution of Augmenting Topologies) is an encoding method that evolves artificial neural networks (ANNs) with the same principles as the method it is based upon, NEAT (NeuroEvolution of Augmenting Topologies). It's advantage over standard NEAT is it's ability to exploit the geometry of a task by mapping it onto the topology of the underlying network. This allows the problem to be shifted away from issues of dimensionality, and towards underlying problem structure. In addition, the encoding employed (CPPNs or Compositional Pattern Producing Networks) can represent the same network at any resolution, allowing for ANN's to scale far better.

Other NeuroEvolution methods exist and have been used to perform many studies over the years, such as NEAT[28], which also already exists within the simulator that is being used. HyperNEAT-M was chosen over NEAT-M with the belief that it would improve performance with it's scaling capabilities.

It has been observed that there is far more work that has been done in experimenting with co-evolving controllers/behaviour and morphology for single robots[26][12][23][22][10][3] much less work has been done in cooperative or multi-robot systems[2][14][20][7]. In order to broaden this field that is in recent years becoming more popular, Cooperative robotics was chosen as the problem area to work with.

Multi-Objective Evolutionary Algorithms (MOEA's) and related optimization techniques have existed for some time now, and have been used to tackle various problems with much success[34][20][18]. In particular, Lim et al. was able to show that for some solutions, Robots evolved using MOEA's outperform those using Single-Objective Evolutionary Algorithms (SOEA's)[18]. Recently, Nagar et al. was able to make interesting findings regarding the effects of imposing a cost on complexity upon evolved robot systems, using a MOEA. [20]

The caveat here is that the current model of evolution by natural selection in biology[31] posits that it does not work according to the rules of Multi-Objective optimization, and rather there is the single objective (the ability to pass on your genes), and everything else is an objective as a consequence of that single objective which exerts selection pressure. The simulation of evolution in order to draw interesting conclusions relating to biology needs to be done using a SOEA then. In addition, Nagar et al. uses a MOEA for one test and compares it to a SOEA, without controlling for possible differences in results obtained purely from comparing a MOEA and a SOEA, which Lim et al. has shown can occur.

It is for these reason that this study chooses to investigate the cost of complexity using a simulated battery-draining mechanism, designed as a proxy for complexity.

3 METHODS

This study will test it's research objectives by comparing results obtained by evolving homogeneous robots with sensor costs through HyperNEAT-M and results obtained by evolving homogeneous robots without sensor costs through HyperNEAT-M. These robots will simultaneously be evolved through different environment difficulty. Robots are homogeneous in that each robot in a generation has the same morphology and neurology (underlying Artificial Neural Network controller).

The simulator used has MASON groundwork[19] with some extensions that have been added by previous works over the past few years [20][15]. This study further extends the simulator by providing options for imposing an energy cost on sensors, or neurology, or both. This is functional when combined across all other parameters. Going with this, the robots have inherent battery packs in the simulation, and when their energy costs run out they stop all functions, and are essentially 'dead'. The energy costs on sensors only will be activated here as morphology complexity is what is being tested.

A population of homogeneous robots will be placed randomly in a collective robotics task-environment, allowed to perform for a set number of timesteps, after which their task performance will be recorded. This process will be repeated 5 times for each generation and the average will be recorded as that generation's average. The generation will then be evolved using the HyperNEAT-M algorithm to create a new generation. This process will then repeat for a set number of generations

This will then be repeated but with the robots' energy costs activated. If a robot should run out of energy before their set number of timesteps expires, they will cease to be able to move or perform, disallowing them from making actions to improve their task performance further. The battery is refreshed when they are placed in the environment once again.

In terms of energy costs choices, these energy costs for morphology were implemented by tying it to the sensors that the robots evolve. The sensor with the most field of view, range and accuracy was chosen to have a energy cost value of 10, and the weakest sensor in the above metrics was given a sensor cost of 1. The rest of the sensors had sensor costs attributed to them scaling in a similar manner. This was then tested with populations that had been previously evolved [20] and it was determined that the cost was adequate for investigating the research objectives.

In terms of task-environment, a collective task-environment was chosen. Robots are placed randomly in a square two-dimensional 'field' as well as blocks of varying sizes (depending on environment difficulty: small, medium, large). The objective is for the robots to move the blocks (by pushing) into the gathering zone, a zone comprising one area of the field. Some blocks require more than 1 robot to push them (medium and large blocks), and robots are expected to cooperate to achieve this. task performance is then evaluated as a function of the number of blocks within the gathering zone at the end of each replication.

A collective task-environment was chosen as it is a fairly well established field that has been investigated for some time [5][17]. It is also very relevant to possible future real life robot use, such as space travel [6] or search and rescue [8].

3.1 HyperNEAT-M process

Figure 1 shows broad step-by-step pseudo-code of the evolutionary process using HyperNEAT that robots are evolved using.

At the end of this, it is then repeated as per the for loop with argument 'numGenerations' (this loop is run 250 times for 250 generations).

'aggregateTaskPerformance(trials)' represents the point at which the mean, max and min of task performance of the 5 trials is recorded, and the following line logs it as scores.

It can be seen in the while loop that if either the maximum lifetime is reached, or battery life is expended, the robots will no longer take input from sensors and receive movement commands from the CPPN, which means they are effectively 'dead' and will no longer be able to improve their current task performance.

```
InitializeEnvironment

InitializeRobotFactory

for (numGenerations)

    for (popsize)

        PlaceRobotRandomly(OutsideGatheringZone)

        InitializeRobotNeurology(InitialConnectionDensity,Substrate)

        InitializeRobotMorphology(oneOfEachSensor)

    for (eachBlock)

        PlaceBlockRandomly(OutsideGatheringZone)

    for (trials)

        While (Timestep<10000 & Batterylife>0)

            for (eachRobot)

                CPPN.takeInput(AllSensoryInput)

                Robot.Move(CPPN.generateOutput)

            if (ComplexityCostEnabled)

                Batterylife-=Robot.getSensorCosts

            Timestep++

        EvaluatePerformance(numBlocksInGatheringZone & typeBlocksInGatheringZone)

    aggregateTaskPerformance(trials)

    Score.log(taskperformance,sensors,neurology)

    for (potentialSubstrateConnections)

        FeedIntoCPPN(SubstrateCoordinatePair)

        WeightOfConnectionPair.setTo(output)

    applyEvolutionModifiers() //These are the Mutation Operators in Table 1
```

Figure 1: Brief pseudo-code of evolutionary process

Crossover rate		0.32
Probability to apply a mutation operator		0.34
Mutation Operators' selection rate	Sensor weight perturbation	0.08
	Add / Remove sensor	0.07
	Sensor position / Orientation perturbation	0.07
	Sensor FOV / Range perturbation	0.07
	Add / Remove hidden node	0.05
	Add / Remove connection weight	0.05
	Connection weight perturbation	0.335
Generations per experiment		250
Trial (robot lifetime) evaluations per generation		5
Population size		150
ANN connection weight range		[-1.0,1.0]
ANN Hidden, output nodes		Sigmoidal
ANN Input nodes		Sensor input: [0.0,1.0]
Initial Connection Density		0.9
Initial Sensory Input Nodes / Ouput Nodes		5 / 2
Output Nodes		2
Minimum sensor placement distance (Portion of chassis circumference)		0.01

Table 1: Neuro-Evolution Parameters

Block size	Small	0.01 x 0.01
	Medium	0.015 x 0.015
	Large	0.02 x 0.02
Sensor Types : Range / FOV	Ultrasonic	(0.0,1.0] / (0.0,π)
	Infrared Proximity	(0.0,0.4] / ($\pi/6, 5\pi/6$)
	Color	(0.0,0.4] / ($\pi/6, 5\pi/6$)
	Low Res Camera	(0.0,0.8] / ($\pi/9, 8\pi/9$)
	Gathering Zone Detection	Bottom facing
Sensor bearing range	[-π, π]$Radians$	
Sensor orientation range	[-$\pi/2, \pi/2$]$Radians$	
Robot lifetime (Time-steps per sim. task trial)	10000	
Battery capacity	100000	
Robot group size	20	
Robot size (Diameter) / Gripping distance / Speed (per time-step)	0.004 / 0.002 / 0.013 (As portion of environment size)	
Initial robot / block positions	Random (Outside gathering zone)	
Environment width x height / Gathering zone width x height	1.0 x 1.0 / 0.5 x 0.2	
Minimum / Maximum number of sensors	1 / 10	
Task environments (Blocks: small, medium, large)	Simple	10,5,0
	Medium	5,5,5
	Difficult	0,5,10
Co-operation needed for block pushing (based on block)	Small	1 Robot
	Medium	2 Robots
	Large	3 Robots

Table 2: Task-environment parameters

4 EXPERIMENT

The experiment consisted of 30 runs completed using HyperNEAT-M with sensor energy costs across the 3 difficulties, as well as 30 runs without sensor energy costs. The metrics of morphological complexity, task performance and trends in the rate of evolution were measured, to allow for comparisons. The parameters used in the experiments can be seen in Table 1 and Table 2. They were largely chosen to make this study's results comparable to previous work [20] and all other parameters not listed were made to be the same as in previous work as well. [15]

Each run consisted of 250 generations, each generation consisted of 5 replications. Each replication was a full 10 000 timesteps that the robots existed for in their environment, to perform activities and demonstrate task performance.

task performance was evaluated at the end of the 5 replications (before evolving to the next generation using HyperNEAT-M) using the following equation:

$$T = 100 \times \frac{Vc}{Vt} + 10 * (1.0 - \frac{Se}{St}) \tag{1}$$

Where Vc is the number of blocks at the end of the replication that are in the gathering zone, Vt is the number of total blocks that are in the environment, Se is the number of time-steps in the robots' lifetime (10 000) and St is the total time-steps per generation (50 000). Finally, T is the evaluated task performance.

The 5 replications exists to allow the robots to experience a variety of starting positions as well as varying the block starting positions, to take into account some random variation that may be influenced by this. Each replication has exactly the same parameters and populations, with only the starting positions being varied randomly.

The different sensor costs are shown in Table 5. These were decided upon based on their relative fields of view as well as usefulness, and tested upon a few populations generated without energy costs to determine that they were reasonable.

Figure 2 shows the robot structure on the left and centre, and the robots acting within the environment on the right. Within the robot structure we can see the sensors being represented, this is in fact the starting configuration of robots when they are initialized for the first generation. They are initialized with one of each sensor, and can mutate to add or remove sensors as per the mutation rates shown in Fig 2.

5 RESULTS AND DISCUSSION

The Results were arranged into a series of boxplots to showcase the interesting differences found between groupings in terms of task performance, Morphology, and the effect task-environment difficulty has on the former two. Figure 3 and 4 show the compared spread of results categorized by cost or no-cost. Values are normalized to between 0 and 1, with higher values (closer to 1) meaning more complex sensor-morphology in Figure 3 and more fit in Figure 4. Lower values (closer to 0) imply more simple sensor-morphology in Figure 3, and less task performance in Figure 4.

We can see clearly from the spread of data in Figure 3 that as is the intuitive answer, imposing a cost on complexity generally results in reduced complexity evolved in the robot bodies and simpler morphologies dominating (49% decrease in mean with complexity costs than with no complexity costs). This is strong evidence for the hypothesis that a cost imposed upon complexity results in the evolution of simpler morphologies.

In Figure 4 we can see that evolved task performance is generally worse in robots evolved with complexity costs (16% reduction in mean), however the difference appears with this data to be less than that in Figure 3. The trade-off is certainly not perfect, implying that some efficiency is lost/wasted in robots that evolve without complexity costs.

Figure 5 and 6 show the spreads of results categorized by difficulty, and it's effect upon evolved task performance in the robots. Values are normalized between 0 and 1. Higher values (closer to 1) in Fig.5 and 6 indicate better evolved task performance, and lower values (closer to 0) indicate worse task performance.

It is apparent that most of the difference in task performance comes within the more difficult task environments, the simple environments differ by only 4% in mean. The difficult task environment task performance with complexity costs is reduced by 28% from no complexity costs, and the medium of the same is reduced by 22%.

Figure 7 and 8 show the spreads of results categorized by difficulty, and it's effect upon evolved sensor morphology (as per this paper's definition). Figure 7 shows these results from runs with sensor-complexity cost imposed, and Fig 8. shows these results from runs without sensor-complexity cost imposed. Values were normalized to a scale from 0 to 1, with values closer to 1 indicating more complex robot sensor morphology, and values closer to 0 having robots with less complexity.

We can see comparing Figure 7 and 8 that a cost imposed upon sensor morphology does result in simpler morphologies being evolved, as in Figure 7 the spreads are markedly closer to 0, as well as having less variance than those without a complexity cost, in Figure 8. This is pertinent information for the research objective and adds weight to the hypothesis that costs imposed upon complexity result in robots with simpler evolved morphologies.

Most of this difference is attributed to simple and medium task environments (54% reduction in morphological complexity in complexity cost simple task environment from no-cost, 51% reduction in morphological complexity in complexity cost medium task environment from no-cost), with a marked difference also in difficult task environments, albeit lesser (42% reduction in morphological complexity in complexity cost difficult task environment.)

The effect environment difficulty has here is also of interest, it is apparent that individuals evolved without complexity costs within simple environments developed more complex morphologies naturally, than those evolved within difficult environments (19% reduction in sensor complexity from simple to difficult task environment).This is in line with some previous work [3].

Welch t-tests [33]were performed to test for difference in means of task performance and morphology between sensor-complexity cost and no sensor-complexity cost evolved robots, and the results can be seen in the Tables 3 4. Welch t-tests were chosen over standard t-tests due to unknown variances in the robot means, and the assumption that they are under-appreciated for their statistical power[25].

Statistical test show ($p<0.05$) that for all task-environments, evolved robots using sensor-complexity costs perform worse (have lower evolved task performance) than robots evolved without sensor-complexity costs. This is more pronounced at higher difficulties.

These results reinforce those of previous work [29][30][3][20] finding that increased environmental difficulty does not necessitate increased morphological complexity. In actuality, these results hint that increased environmental difficulty pushes for simpler morphologies when a complexity cost is not used, as shown in Figure

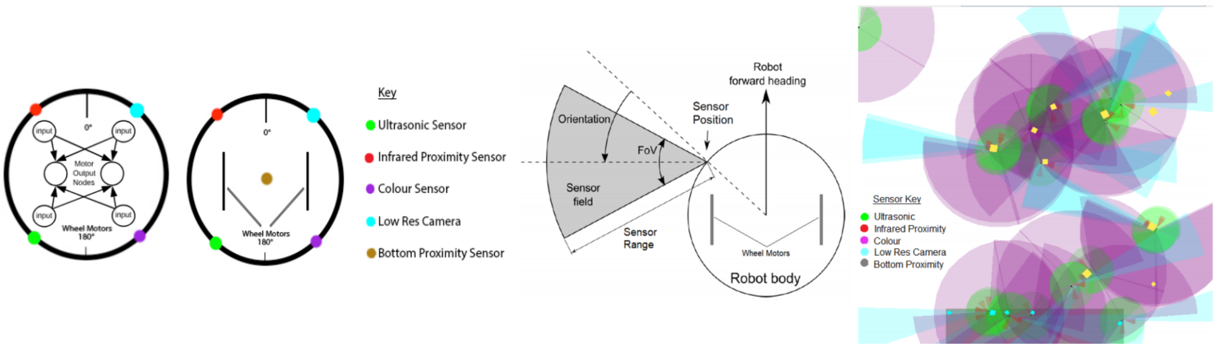

Figure 2: Left: The Robot represented as a diagram showing the various sensors. Centre: The Robot's Orientation and sensor optic shape. Right: The Robots acting within their environment, sensor periphery shown as cone shapes, blocks as yellow squares, robots as black dots and shaded rectangle as gathering zone. From Furman et al.[20]

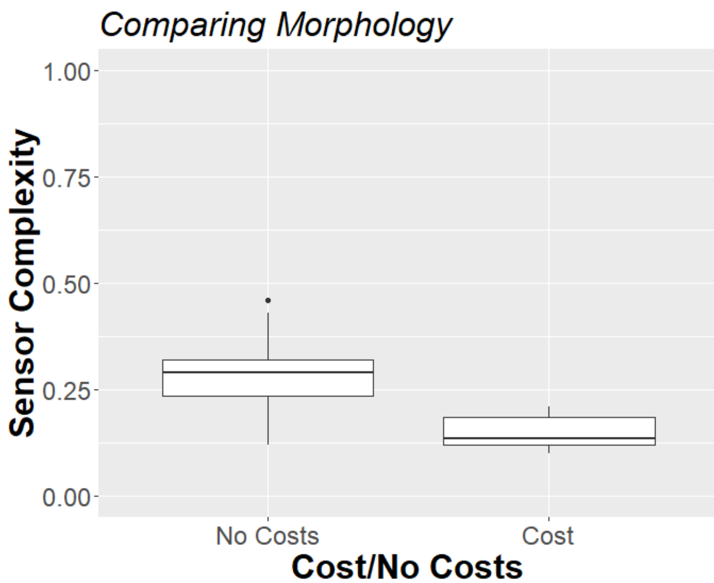

Figure 3: Boxplot showing the effect morphological (Sensor Complexity) cost has on evolved morphology. Higher is more complex.

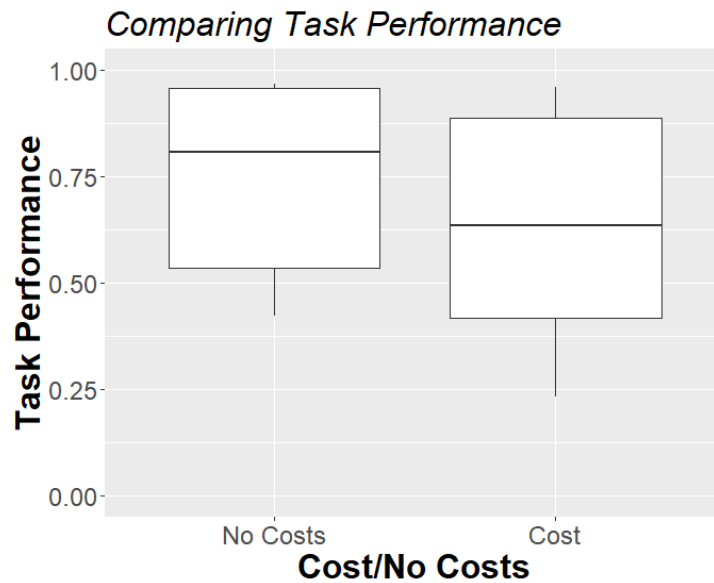

Figure 4: Boxplot showing the effect morphological (Sensor Complexity) cost has on evolved task performance. Higher is more fit.

Difficulty	Complexity Cost Result
Simple	<
Medium	<
Difficult	<

Table 3: Result of t-tests for difference in means in task performance between robots evolved with and without a cost on complexity. '<' implies that complexity cost imposed mean is less than those with no complexity costs (p<0.05).

Difficulty	Complexity Cost Result
Simple	>
Medium	>
Difficult	>

Table 4: Result of t-tests for difference in means in complexity between robots evolved with and without a cost on complexity. '<' implies that average complexity is less than those with no complexity costs (p<0.05).

Sensor	Energy Cost
Proximity	1
BottomProximitySensor	1
ColourProximitySensor	2
Ultrasonic	5
LowResCamera	10

Table 5: Sensors and their energy costs.

8. In essence, these results are hypothesized to be heavily dependent on the definition of morphological complexity used in the evolutionary process (implementation of complexity costs) as well as the definitions used to test hypothesis upon the evolved population. This is in line with related work [3][20][4][15] which all utilize different definitions of morphological complexity. For example, Nitschke et al. [20] used a morphological definition comprising the field of view and range of the sensors, and found evidence that increased task difficulty for robots given complexity costs (using a multi-objective approach) resulted in robots with simpler morphologies. The results in Figure 6 find that this is not the case.

In the case of this study, complexity was only looked at from a morphological standpoint, and was defined as the hypothetical value drained per unit timestep by the robots, a value based upon individual weightings given to each sensor based upon it's inherent usefulness and power. To simplify, complexity costs were imposed as energy costs proportional to the complexity of the sensor, (Table 1). The higher the sensor complexity, the less lifetime a robot team had (as more energy was drained) and thus less time with which to complete tasks.

The key value of this study's implementation of complexity costs is in it's ability to avoid multi-objective methods, and focus on single-objective evolution, as is the standard model for biological evolution.

This study in summary contributed further investigation and looking around into the relationships between task complexity, task performance, and morphological complexity to add on to help build upon previous works of similar natures [20][3][4][15], and did so using a different angle of approach in the form of single-objective implementation of complexity costs within the context of evolution.

6 CONCLUSIONS

This study investigated the relationships between morphological complexity, task complexity and their effects upon task performance in an evolutionary collective robotics environment. Experiments evaluated task-performance in a collective cooperative robotics task and evolution was performed using HyperNEAT-M. Analysis was performed upon the results drawing to some interesting conclusions, such as the finding that for all difficulties, complexity costs yield less complex robots, yet also yield robots with weaker task performance. In addition, it was found that simpler task-environment difficulties result in the development of more complex morphologies, at least in the context of this paper's morphological complexity definition, yet this is only in the case of complexity costs not being imposed upon the population.

This study also manages to attack this investigation from a new angle of approach, utilizing single-objective evolutionary methods while still enabling complexity costs through a simulated battery draining mechanism as a proxy. This is an interesting and important change from past investigations [20] as it is much more true to 'real life' or biological evolution.

However, this field of research still has many open questions regarding different implementations of various meta-parameters such as complexity costs, task difficulties and methods of evolution itself, making it still an important area of ongoing research.

6.1 Future Work

The following is 3 hypothesized future work goals (and their explanation) that could prove extremely beneficial to the field with their exploration:

(1) **Tying the cost of complexity to something more meaningful.** As it stands, the complexity costs were tied to improvised sensor costs that were only thought of at the time as being representative of the usefulness of the sensor. A more meaningful relationship could and should be explored, such as tying them to sensor FOV (field of view) and range, or adapting it from real life sources such as the Khepera manual.

(2) **Investigating the rate of evolution and complexity costs' effects upon it.** This study effectively only investigates the end results of the evolutionary process, and the speed and efficiency at which evolution occurs is not looked at at all. This could prove interesting, if interesting advantages in the respect of complexity costs are found.

(3) **Investigating neurological complexity costs.** Morphological complexity costs were only considered in this study, and neurological complexity was ignored entirely. A study with a similar angle of approach which investigated neurological instead of morphological complexity could prove useful and beneficial to the field.

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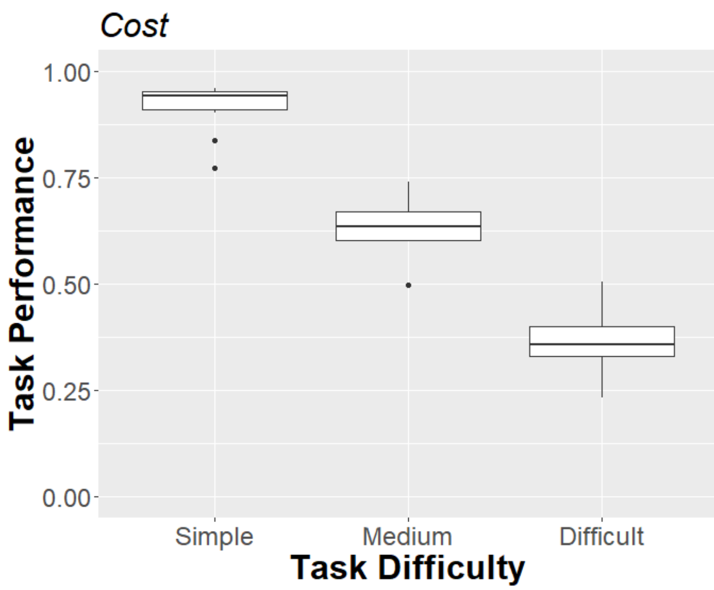

Figure 5: Boxplots showing the impact task-environment difficulty has on task performance for robots evolved with a complexity cost. Higher values are more fit.

Figure 6: Boxplot showing the impact task-environment difficulty has on task performance for robots evolved without a complexity cost. Higher values are more fit.

Figure 7: Boxplots showing the impact task-environment difficulty has on sensor morphology for robots evolved with a complexity cost. Higher values are more complex.

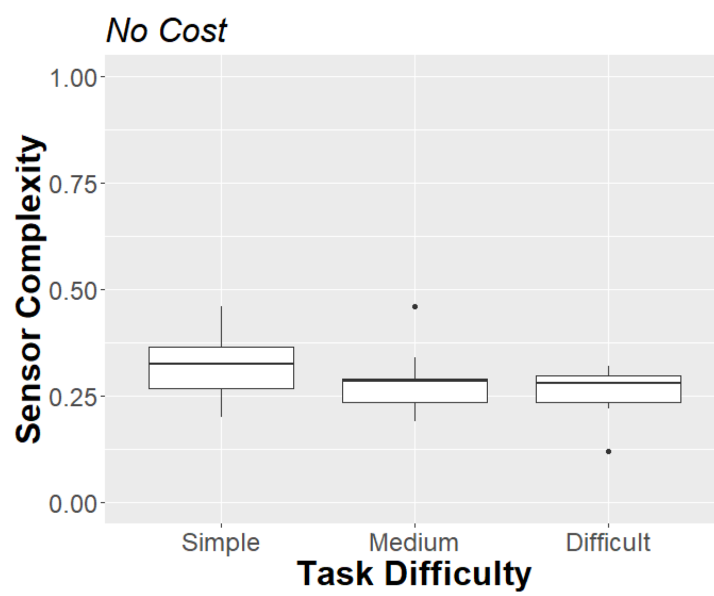

Figure 8: Boxplot showing the impact task-environment difficulty has on sensor morphology for robots evolved without a complexity cost. Higher values are more complex.

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