The Cost of Big Brains in Groups

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Abstract

The *social brain hypothesis* posits that the evolution of big brains (neural complexity) in groups of social organisms is the evolutionary result of cognitive challenges associated with various complex interactions and the need to process and solve complex social tasks. This study aims to investigate the environmental and evolutionary conditions under which neural complexity evolves without sacrificing collective behavioral efficacy. Using an evolutionary collective robotics system this research evaluates the impact of imposing a fitness cost on evolving increased neural complexity in robot groups that must operate (accomplish cooperative tasks) in environments of varying complexity. Results indicate that for all environments tested, imposing a cost on neural complexity induces the evolution of smaller neural controllers that are comparably effective to more complex controllers.

Introduction

The fitness costs of evolving neural complexity (neural tissue) needed for socially adaptive behaviour are critically important to brain evolution (Azevedoand and Houzel, 2012). Various neuroscience studies have demonstrated that increased neural complexity is metabolically expensive (Laughlin et al., 1998), though there are conflicting hypotheses about how the increased fitness costs of larger brain sizes (increased neural complexity) is compensated for in evolution (Armstrong, 1983), (Isler and van Schaik, 2009). Also, the environmental and evolutionary conditions driving the evolution of such complexity in the first place remains an open question (Fisher, 1930).

In some species of organisms it is hypothesized that evolved brain size (neural complexity) is correlated to the size, structure and complexity of social groups formed by such species (Dunbar and Shultz, 2007). The *social brain hypothesis* posits that the evolution of such neural complexity is a result of the cognitive challenges associated with varied and complex interactions and the need to process complex social information (Dunbar, 2009).

Studies of various social organisms including ant colonies (Kamhi et al., 2016), have supported the social brain hypothesis via demonstrating that socially complex behavior such as division of labor and cooperation (collective intelligence) are likely driving forces of brain complexity evolution. However, there is also contradictory evidence in such studies as related work on other ant species (Feinerman and Traniello, 2016) elucidated the evolution of smaller brains (lower neural complexity) in groups of workers that were still able to collectively perform complex collective behaviors that supported and benefited the colony. In both cases, the exact impact of the environment and complexity of cooperative tasks (supporting group survival), on the evolution individual neural complexity and thus the group's social complexity, remains little investigated and unclear in the context of natural and artificial life (Yaeger, 2009).

This research takes inspiration from such evolutionary biology studies, and uses collective *evolutionary robotics* (Doncieux et al., 2015) as an experimental platform to test the impact of varying environment complexity (collective behavior task difficulty) on the evolution of neural complexity. This study tests the *social brain hypothesis* using robot groups, where behaviors are specified by evolved neural controllers and robots interact to cooperatively solve *collective gathering tasks*. Thus, we evaluate the impact of imposing fitness costs on evolving neural complexity in robot groups that must solve increasingly difficult collective gathering tasks, where task difficulty is the degree of cooperation needed for task accomplishment.

In this study, the cost of evolving increased robot neural controller complexity is tantamount to metabolic energy costs associated with increased brain sizes in nature (Armstrong, 1983; Laughlin et al., 1998; Isler and van Schaik, 2009). This study's core motivation is the general lack of understanding (across various fields including evolutionary biology and robotics) of how environment driven necessity for social complexity (for example, emergent collective behaviors and social structure in groups) impacts brain size and structure (Farris, 2016).

Various approaches for evolving neural complexity have been studied in related research topics such as *computational ecologies*, where for example, Williams and Yaeger (2017) demonstrated complexity evolution without explicit fitness costs. Fitness cost impact on complexity evolution has also been demonstrated in *simulated sensor systems* (Seth and Edelman, 2004), and with *neural modularity* (Clune et al., 2013; Lowell and Pollack, 2014). However, there are few evolutionary collective robotics studies that investigate the impact of environment complexity on evolving controllers given a complexity cost (Doncieux et al., 2015). This is significant as evolutionary collective robotics (Bredeche et al., 2018) allow experimenters to investigate competing hypotheses pertinent to, but not readily testable in natural social systems. That is, the social brain hypothesis is more suitably evaluated in embodied cognition systems such as evolutionary robotics given that such systems can readily implement controlled and testable *distributed* and *embodied* theories of cognition (Barrett et al., 2007).

This study thus aims to elucidate the advantages and disadvantages of imposing a fitness cost on evolving controller complexity (neural connectivity) in an evolutionary collective robotics system (Doncieux et al., 2015). Neural complexity is defined by evolved controller topology (connectivity between sensory, hidden and output nodes) and evaluation was evolved collective gathering behavior task performance. Given this and the social brain hypothesis, we formulated the following research objective.

To evaluate the impact of fitness costs on evolving neural controller complexity given increasing collective behavior task difficulty in collective robotics. We thus aim to ascertain if the social brain hypothesis holds for an evolutionary collective robotics system that must operate and accomplish cooperative tasks in environments of varying complexity.

Methods

This study evaluated *NEAT-M* (Hewland and Nitschke, 2015) controller-morphology neuro-evolution versus the *NEAT-M-MODS* multi-objective extension. Both methods co-adapted robot *Artificial Neural Network* (ANN) controllers and sensory-morphologies for given tasks. Groups were homogenous as the same behavior-morphology adaptations were applied to all robots in a group. Behavior-morphology evolution with NEAT-M-MODS included a *neural complexity cost* (section: *Neural Complexity*), imposed during neuro-evolution. This was represented as the minimization of neural complexity, in company with the maximization of collective gathering task performance, as part of multi-objective optimization. These objectives thus encouraged the evolution of minimally complex and behaviorally effective neural controllers. NEAT-M was comparatively evaluated, where it only maximized collective gathering task performance, in order to ascertain the impact of a neural complexity cost during evolution.

NEAT-M-MODS: Overview

Neuro-Evolution for Augmenting Topologies (NEAT)-M-MODS is a multi-objective extension of NEAT-M (Hewland and Nitschke, 2015) and NEAT-MODS (Abramovich and Moshaiov, 2016). NEAT-M evolves a direct encodings of both robot ANN controllers and morphologies (ANN connections to sensory input nodes constituting a robot's sensory configuration). NEAT-M-MODS supersedes the core functionality of NEAT-M (Hewland and Nitschke, 2015) via including an NSGA-II based *Multi-Objective Evolutionary Algorithm* (Abramovich and Moshaiov, 2016), that uses multiple objectives to direct the evolutionary process of NEAT (Stanley and Miikkulainen, 2002).

NEAT-M-MODS initializes a genotype (controller-sensor) population, computes each genotype's score vector (multi-objective fitness), speciates the population and computes a *rank* for each genotype based on *non-dominated sorting* and *crowding distance comparisons* (Doncieux and Mouret, 2014). This process, evolutionary operators and parameters are detailed in Furman et al. (2019) and NEAT-MODS is described in Abramovich and Moshaiov (2016).

Neural Controller-Sensor Evolution

For both neuro-evolution methods (NEAT-M, NEAT-M-MODS), robots began with a minimal sensory configuration of five sensors (one of each type), each sensor corresponding to a controller input node. Input nodes were fully connected to two motor output nodes (figure 1, left). Connections were randomly initialized and without any hidden layers and controllers subject to *complexification* during neuro-evolution. Controllers used sigmoidal (Hertz et al., 1991) hidden and output nodes and all sensory inputs were normalized to the range: [0.0, 1.0].

Figure 1 (center-left) presents the initial robot controller-sensory configuration used as an evolutionary starting point for both NEAT-M and NEAT-M-MODS. This initial controller-sensor configuration (motor outputs were fixed during evolution) was selected so as robots performed some useful behaviors at the start of the evolutionary process. The possible sensor types were: (1) *Ultrasonic*, (2) *Infrared Proximity*, (3) *Color*, (4) *Low Resolution Camera*, and (5) *Gathering Zone Detector* (table 1). These sensors were selected as they are typically available for the Khepera III mobile robot (Lambercy and Tharin, 2013). Parameters for all sensor types were perturbable by mutation operators that add and remove sensors (of a given type), as well as modify, add and remove ANN connection weight values, add and remove weight connections to sensors, and change sensor positions and orientations (on the robot's periphery).

Table 1: Experiment and Simulation 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	$(0.0, 1.0]$ / $(0.0, \pi)$
	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	$[-\pi, \pi]$ Radians	
Sensor orientation range	$[-\pi/2, \pi/2]$ Radians	
Robot *lifetime* (Time-steps per simulation task trial)	10000	
Robot group size	20	
Robot size (Diameter) / Gripping distance / Speed (per time step)	0.004 / 0.002 / 0.013	
Initial robot / block positions	Random (Outside gathering zone)	
Environment width x height / Gathering zone size	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
Cooperation needed for block pushing	Small	1 Robot
	Medium	2 Robots
	Large	3 Robots

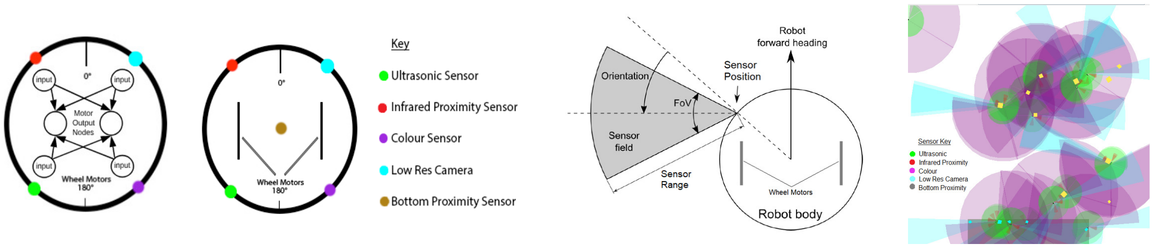

Figure 1: **Left:** Initial robot controller connecting 5 sensors to 2 actuators. **Center-Left:** Robots were initialized with one ultrasonic, infrared proximity, color, gathering zone detector (bottom proximity) sensor and one low-resolution camera. Wheel motors were fixed throughout controller evolution. **Center-Right:** Example robot with one sensor. Position determines sensor location on the robot's chassis with respect to the robot's heading. Orientation is then sensor direction with respect to this position. By default, a robot's heading is forward facing (parallel to its wheels). **Right:** Environment with 20 robots and distributed blocks. The *gathering zone* containing gathered blocks (blue squares) is highlighted at the bottom. Sensory parameters (type, position, orientation, field of view and range) are highlighted as shaded semi-circles.

Mutation operators are presented in Furman et al. (2019). The parameter-set for each sensory input node is: *Sensor Type*, *Field of View* (FOV), *Range*, *Position*, and *Orientation*. Figure 1 (center), presents an example robot with one sensor and an illustration of sensor parameters.

Neuro-evolution was driven by genetic, that is, *crossover* and *mutation* operators. These operators adapted ANN connection weights and added or removed hidden or input nodes. This adapted the number of sensors or otherwise perturbed sensor parameters. At each generation (of NEAT-M and NEAT-M-MODS), either crossover or mutation operators were applied with a given degree of probability. The crossover and mutation operators are described in previous work (Hewland and Nitschke, 2015; Furman et al., 2019). If a new sensor was added (*add sensor* operator) it was placed at a given minimum position distance between two randomly selected sensors already on the robot's chassis. If there was only one sensor currently on the robot's body the new sensor was placed randomly to the left or right of this one sensor. The same procedure was followed for the *remove sensor* operator, where at least one sensor had to be positioned on a robot's chassis.

Two wheel motors controlled a robot's heading at constant speed. Movement was calculated in terms of real valued vectors (*dx* and *dy*). Wheel motors (figure 1, center-left, center-right) were explicitly activated by the ANN and a robot's heading was determined by normalizing and scaling output values by the maximum movement distance for one simulation time-step (Hewland and Nitschke, 2015).

Neural Complexity Definition

Neural complexity[1] is defined as the number of connections n ($n \in [0, 120]$) in an evolved neural controller (at generation g) and thus includes all connection weights linking sensory input nodes to hidden and output nodes. This neural complexity definition was adapted from related work (Nitschke and Didi, 2017) and selected for its simplicity and accounting of sensory (morphology) complexity with

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[1] *Neural simplicity* is synonymous in this article's discussion.

respect to the neural controller. Thus, the more complex a robot's sensory morphology, the higher its controller's neural complexity will be. That is, this definition assumes sensory input nodes are connected to hidden or output nodes.

Collective Gathering Task

Collective gathering requires robots to locate distributed resources (blocks) in a bounded environment and transport them, via cooperative pushing, to a *gathering zone* (Nitschke et al., 2012). This task was selected given that relatively sophisticated collective behaviors (enabled by suitably complex controller-morphology couplings of interacting individuals) are required to solve such cooperative tasks (Nitschke, 2005). Also, collective gathering is an established collective evolutionary robotics benchmark task and is thus a suitable experimental platform for evaluating neural controller evolution (Doncieux et al., 2015).

Cooperation was defined as the number of robots required to push given block types and *task difficulty* was a function of the *number of blocks*, *block types* and *cooperation* needed. Block types were *small*, *medium*, or *large*, to be pushed by at least one, two and three robots, respectively (table 1). Task difficulty was calibrated via initializing environments (simple, medium, difficult) with varying combinations of block types (table 1). For example, the *simple* environment contains 10 small and 5 medium sized blocks, so robots could work concurrently with minimal cooperation to move all blocks into the gathering zone. Collective gathering task performance was the total number of blocks pushed into the gathering zone during the robots' *lifetime* (table 1).

Experiments

Experiments measured the impact of a neural complexity (fitness) cost versus no such complexity cost imposed during controller-sensor (morphology) evolution in robot groups tasked with solving collective gathering tasks of increasing difficulty. NEAT-M-MODS used multi-objective controller evolution (task performance maximization and complexity minimization), and NEAT-M used single objective (task performance) optimization. The experimental platform was a collective robotics simulator (Hewland and Nitschke, 2015) implementing the collective gathering task (figure 1, right). Robots emulated the Khepera III (Lambercy and Tharin, 2013), with co-adapting controllers and sensor configurations[2]. Experiments ran simulations of 20 robots in bounded two dimensional continuous environments with distributions of *small*, *medium*, and *large* blocks (table 1).

Blocks were randomly distributed throughout an environment, excluding the *gathering zone*. Block type distributions given in table 1 correspond to increasing environment complexity (*simple*, *medium*, *difficult*) designed to test the impact of environment complexity on controller evolution with and without a neural complexity cost. Robots were initially randomly placed in the gathering zone.

To test this study's research objective we designed two experiment sets. Experiment set 1 evaluated the impact of a neural complexity cost on controller evolution via evaluating NEAT-M-MODS evolved groups in all environments (table 1). Comparatively, experiment set 2 evaluated controller evolution without a neural complexity cost. That is, NEAT-M evolved groups were evaluated in the same environments. Only homogenous teams were tested, meaning that at each NEAT-M and NEAT-M-MODS generation, selected controller-sensor adaptations were copied 20 times (representing group sizes of 20 robots).

Fitness Function

In experiment set 1, task performance was maximized and neural complexity minimized. This second objective encouraged lower neural complexity, thereby imposing a *fitness cost* on controller complexity. In experiment set 2, only task performance was maximized. Task performance was the average *value of blocks* pushed into the gathering zone over five robot *lifetimes* comprising each generation.

We defined v_c as total value of resources (blocks) in the gathering zone, v_t as total value of all resources in the environment, s_e as the number of simulation time-steps in the robots' lifetime and s_t as number of trial evaluations per genotype (controller-sensor configuration). As such, task performance T was maximised using equation 1:

$$T = 100 \times \frac{v_c}{v_t} + 20 \times (1.0 - \frac{s_e}{s_t}) \tag{1}$$

In equation 1, 100 was the maximum number of blocks that could be gathered during an experiment run, and 20 was an experimentally determined weighting (boosting fitness for efficient individual and cooperative gatherers).

Each experiment applied NEAT-M or NEAT-M-MODS to evolve collective gathering behavior for 200 generations. A generation comprised five robot lifetimes, where each lifetime was 10000 simulation iterations. Each lifetime was a simulated collective gathering task scenario that tested different robot starting positions, orientations, and block locations in either a *simple*, *medium* or *difficult* environment (table 1). Average collective gathering task performance was calculated at each run's end and averaged over 20 runs. All simulation and neuro-evolution parameters (table 1) were experimentally determined, where those not reported here used the same settings as in previous work (Hewland and Nitschke, 2015; Abramovich and Moshaiov, 2016).

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[2] Simulator & NEAT-M & NEAT-M-MODS source-code is online: https://github.com/costcomplex/anonymous

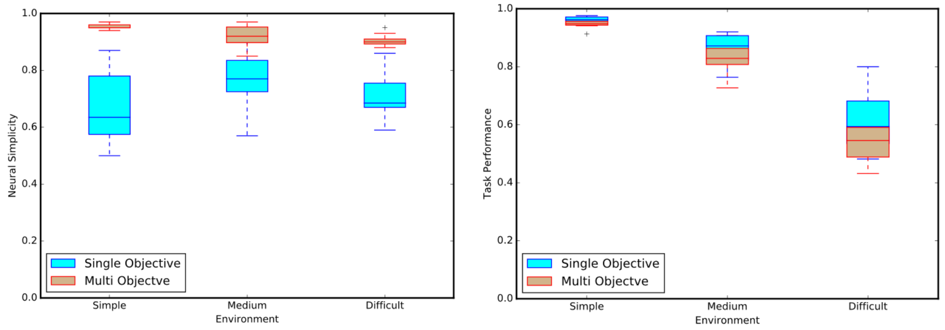

Figure 2: **Left:** Average maximum *neural simplicity* for *Single Objective* (SO): NEAT-M, *Multi Objective* (MO): NEAT-M-MODS (knee-points) for *simple*, *medium* and *difficult* environments, respectively. *Neural simplicity* ~ 1.0 indicates low evolved neural complexity. **Right:** Average maximum task performance of SO: NEAT-M versus MO: NEAT-M-MODS evolved groups.

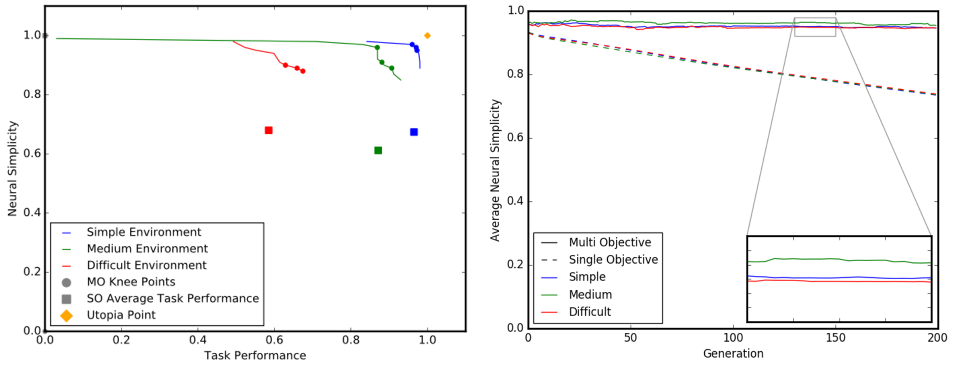

Figure 3: **Left:** Average *Multi-Objective* (MO: NEAT-M-MODS) Pareto front and *Single Objective* (SO: NEAT-M) scores. SO points are maximum task performance and corresponding neural simplicity scores. MO points are the 3 best knee-points. Averages were computed over all runs. **Right:** Progression of average *neural simplicity* for MO and SO over neuro-evolution.

Results & Discussion

Experiments evaluated the impact of a *fitness cost* on neural complexity versus *no cost* during neural network controller evolution in robot groups. Evolved robots were evaluated in terms of collective gathering task performance for increasing difficult environments: *simple*, *medium* and *difficult*. To enable analysis of the neural versus environment complexity trade-off, average neural complexity (and co-adapted sensory-morphology complexity) of the fittest controllers evolved in each environment was also computed. Figure 2 presents average *neural complexity* and *task performance* results. Figure 3 presents *Pareto-front* and evolutionary progression of neural complexity. Results compare these metrics for group behavior evolved *with* (NEAT-M-MODS) and *without* (NEAT-M) a neural complexity cost, across increasingly difficult tasks. Averages were calculated for each environment and over 20 runs for each method.

Figure 2 (left) presents the average *neural complexity*[3] of the fittest controllers evolved by NEAT-M and NEAT-M-MODS in each environment. Neural controller evolution in NEAT-M had a *Single Objective* (SO) of maximizing task performance (fitness), whereas, NEAT-M-MODS had the *Multiple Objectives* (MO) of maximizing task performance and minimizing neural complexity. A neural complexity value of 1.0 indicates the simplest possible controller (one sensor connected to motor outputs) and 0.0 indicates the most complex controller (10 sensors connected to 10 hidden nodes[4] and outputs, table 1). Figure 2 (right) presents average maximum task performance of NEAT-M (SO) versus NEAT-M-MODS (MO) groups evolved in each environment. Calculations for the latter used the three knee-points with the *highest-task performance* and *lowest neural-simplicity* on the *Pareto front* (figure 3, left).

Figure 3 (left) presents the best three *knee-points* for each *Pareto front*. A knee-point was defined as that yielding the highest value for both objectives, where such values

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[3] Note that the term *simplicity* is used in figure 2 for clarity and consistency with related work (Auerbach and Bongard, 2014).

[4] Fixed topology parameter tuning experiments indicated negligible fitness increases in all environments for > 10 hidden nodes.

were closest to the *utopia* point for the simplest and most effective controllers. For comparison, the best SO points (average maximum task performance and matching neural complexity) of NEAT-M evolved groups are also presented. Figure 3 (right) presents the evolutionary progressions of *neural simplicity* for NEAT-M-MODS and NEAT-M groups evolved in each environment. Values close to 1.0 and 0.0 indicate *low* and *high* neural complexity, respectively.

Figure 3 (right) illustrates that groups evolved *with* a neural complexity cost (NEAT-M-MODS) in all environments were consistently comparable, in terms of neural simplicity, throughout neuro-evolution. For clarity, exemplar generations 125 to 150 in figure 3 (right) are enlarged to highlight that the *medium environment* encouraged the evolution of simpler neural controllers (though this difference was not statistically significant). Whereas, groups evolved *without* a neural complexity cost became increasingly complex over the course of neuro-evolution, for all environments. This is supported by statistically significant neural simplicity differences between groups evolved (in all environments) *with* and *without* neural complexity costs (table 2).

Statistical comparisons used *Shapiro-Wilk* (to confirm data normality) and independent *two-tailed t-tests* (Flannery et al., 1986) to test for significant differences ($p < 0.05$) in average task performance and neural complexity (simplicity). Statistical tests were run between respective results of NEAT-M and NEAT-M-MODS evolved groups. The latter used averages calculated from the three *best knee-points* on each Pareto front (figure 3, left).

Statistical comparisons (table 2) of *average neural simplicity*[5] indicated that for all environments, groups evolved *with a neural complexity cost* comprised significantly simpler controllers compared to those evolved *without a complexity cost*. Thus, neuro-evolution with a complexity cost given increasing environment complexity consistently resulted in low selection pressure for complex controller evolution. *Environment complexity* (task difficulty) was a function of the number of blocks and block types, where some degree of cooperation was needed for optimal gathering in all environments (section: *Collective Gathering Task*). Figure 3 (right: evolving average neural simplicity) and figure 2 (left: average maximum evolved neural complexity) further support this result, indicating that neural complexity costs consistently enable the evolution of significantly simpler controllers (versus evolution with no complexity cost). This result is also supported by related work (Lowell and Pollack, 2014) similarly finding that fitness costs on connection weights in NEAT evolved networks produced smaller networks that were just as effective as the best evolved networks without such a complexity cost.

Also, figures 2 and 3 indicate groups evolved without a neural complexity cost resulted in higher neural complexity which in turn enabled higher group task performance (for all environments). However, these task performance differences were negligible for the *simple* environment (SO: 0.96 versus MO: 0.95 in table 2) and minimal for the *medium* (SO: 0.86 versus MO: 0.78 in table 2) and *difficult* (SO: 0.61 versus MO: 0.49 in table 2) environments. Thus, in the *medium* and *difficult* environments, there was an average task performance difference of only 10% between groups evolved with and without a neural complexity cost.

The complexity-fitness trade-off for these minimal task performance differences were significantly less complex neural controllers. Groups evolved *with* a complexity cost in the simple, medium and difficult environments, were 27%, 15% and 22% simpler (table 2, right), respectively. The complexity cost also enabled the evolution of significantly simpler (independent two-tailed t-test, $p < 0.05$) sensor-morphologies coupled with evolved controllers. Sensor-morphologies of groups evolved with the complexity cost were on average, 32%, 35% and 27% simpler, in the *simple*, *medium* and *difficult* environments (respectively). This was compared to the sensory-morphologies of groups evolved without a complexity cost in the same environments.

Sensor-morphology complexity (*simplicity*) was a function of sensors (number and type) and sensor parameters coupled to evolved neural controllers (Furman et al., 2019). For consistency, values were calculated according to *sensory-system simplicity*, where a value of 1.0 indicated one sensor with minimal range and *Field of View* (FOV) and 0.0 indicated a controller with 10 sensors (maximum number) of all types with maximal range and FOV (table 1).

Also, observing the *best knee-point* (figure 3, left) controllers evolved with multi-objective neuro-evolution (incorporating the complexity cost), one notes such controllers had comparable task performances (no statistical difference) in all environments. Thus, even though having no neural complexity cost enabled the evolution of increasingly complex neural controllers[6] (and coupled sensor-morphologies), the added neural and sensor-morphology complexity was largely redundant and unnecessary. This was especially the case when considering the *best knee-point* controllers that evolved to be simple yet effective.

The collective behavior effectiveness of such simple controllers is further theorized to be a result of the nature of task (environment) complexity. Consider that optimal

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[5] *Simplicity* instead of *complexity* is used in this discussion.

[6] Controller topologies evolved with and without complexity costs are online: https://github.com/costofcomplexity/ALIFE2019

Table 2: **Left:** Statistical comparisons for task performance (fitness) and neural complexity of fittest controllers evolved by NEAT-M (SO: Highest task performance) versus NEAT-M-MODS (MO: 3 Knee-points on Pareto-front, figure 3). $>$: Greater than with statistical significance. **Right:** Average task performance and neural simplicity values for groups evolved *without* (SO) and *with* (MO) a neural complexity cost. Neural complexity (simplicity) is defined in section: *Neural Complexity Definition*.

Environment	Task Performance	Neural Simplicity
Simple	SO $>$ MO	MO $>$ SO
Medium	SO $>$ MO	MO $>$ SO
Difficult	SO $>$ MO	MO $>$ SO

Environment	Task Performance	Neural Simplicity
Simple	0.96 (SO) 0.95 (MO)	0.67 (SO) 0.94 (MO)
Medium	0.86 (SO) 0.78 (MO)	0.77 (SO) 0.92 (MO)
Difficult	0.61 (SO) 0.49(MO)	0.71 (SO) 0.93 (MO)

task accomplishment required the group to gather all blocks distributed throughout the environment into a *gathering zone*, within the group's *lifetime*. However, all environments required some cooperation to achieve an optimal or near optimal task performance. For example, the simple environment contained five medium-sized blocks requiring two robots to cooperatively push. The medium environment also contained five large-sized blocks requiring three robots to cooperatively push and the difficult environment included only medium-sized and large-sized blocks. In all environments the efficacy of an emergent cooperative problem-solving behavior was determined by the neural and morphological (sensor) complexity of evolved controllers.

As demonstrated in related work (Waibel et al., 2009; Nitschke et al., 2012; Duarte et al., 2016), we posit that the emergence of effective collective behaviors was enabled by evolved interactions of relatively simple individual controllers. Furthermore, other evolutionary robotics studies have demonstrated evolving increased neural complexity often yields negligible benefits as collective behavior task complexity increases (Nitschke and Didi, 2017).

The overall implication of this study's results is two-fold. First, it indicates that neuro-evolution *with* a neural complexity cost facilitates efficient neural controllers comprising minimal connectivity and simple coupled sensor-morphologies. These controllers were consistently effective for increasing environment complexity (addressing the research objective). Second, results indicated neuro-evolution *without* a neural complexity cost supports the social brain hypothesis in the context of groups surviving in environments of varying complexity. That is, for all environments, groups evolved without a neural complexity cost evolved both significantly larger neural controllers and coupled sensor-morphologies, compared to those evolved with a neural complexity cost. However, the pertinence of the social brain hypothesis was limited in that these more complex neural structures (and sensor-morphology couplings) did not yield clear benefits across all environments.

Specifically, there was negligible group task performance differences in the simple environment and minimal differences ($\sim$10%) in the medium and difficult environments. As presented in figure 3 (left), the best groups (knee-point controllers on the Pareto front) evolved with a complexity cost yielded comparable task performances to groups evolved without a complexity cost, though did so with less neural complexity and simpler sensor-morphologies. Hence, the neural complexity cost was able to suitably complement the *complexification* and *speciation* mechanisms of NEAT-M (Hewland and Nitschke, 2015) via enabling the evolution of simple yet effective controllers. However, without such a complexity cost, NEAT-M complexification ensured the evolution of increasingly complex controllers and coupled sensor-morphologies, where the speciation mechanism was unable to mitigate this evolution of neural complexity.

This study's contribution was two-fold. First, using evolutionary collective robotics to test the impact of a complexity cost, the study supported related work demonstrating that greater evolved social complexity correlates with smaller brains coupled to less complex sensory-systems (Gronenberg and Riveros, 2009). In this study, social complexity was the efficacy of evolved collective behavior across increasingly difficult task environments. Second, results lent empirical support to the use of distributed and embodied cognition systems (Barrett et al., 2007), in this case for the purpose of elucidating the impact of a complexity cost on evolving neural and morphological complexity in social systems.

Conclusion

This study investigated how imposing fitness costs on evolving neural controller complexity impacted evolving collective behaviors in an evolutionary collective robotics system. Experiments evaluated the impact of evolving neural controllers, *with* and *without* a neural complexity cost, on robot group task performance in increasingly complex environments. In this study environment complexity was equated with collective behavior task difficulty. Results indicated that a neural complexity cost enabled the evolution of simpler controllers, where the best of such simple controllers produced collective behaviors comparable to that of more complex controllers evolved without any complexity cost. This result held for collective behavior evolution in task environments of increasingly complexity.

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