The Environment and Body-Brain Complexity

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ABSTRACT

An open question for both natural and artificial evolutionary systems is how, and under what environmental and evolutionary conditions complexity evolves. This study investigates the impact of increasingly complex task environments on the evolution of robot complexity. Specifically, the impact of evolving body-brain couplings on locomotive task performance, where robot evolution was directed by either body-brain exploration (novelty search) or objective-based (fitness function) evolutionary search. Results indicated that novelty search enabled the evolution of increased robot body-brain complexity and efficacy given specific environment conditions. The key contribution is thus the demonstration that body-brain exploration is suitable for evolving robot complexity that enables high fitness robots in specific environments.

KEYWORDS

Evolutionary Robotics, Body-Brain Coevolution, Neural Complexity, Morphological Complexity, Novelty Search

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1 INTRODUCTION

An open question in natural [6] and artificial evolution [38], are the environmental conditions under which complexity evolves. *Evolutionary Robotics* [5] is an effective experimental platform for testing the impact of environmental conditions on evolving complexity given various precepts including the *arrow of complexity* [3] and *social brain* [10] hypotheses. While the impact of varying environments on coevolving body-brain (controller-morphology) complexity has received attention in related fields [17, 38], with notable exceptions [1, 9], it remains little investigated in evolutionary robotics. Elucidating relationships between environments and evolving body-brain complexity is critical considering robot problem-solving behaviors are constrained by brain and body complexity [31]. This yields many benefits for evolutionary robotics [5], for example, in automated evolutionary design applications where robots evolve specially suited designs to problem-solve in specific environments [9, 14, 18].

Some evolutionary robotics studies have investigated the impact of varying environments on evolving either controller [10] or morphological [11] complexity or both [15], given complexity costs. For example, Nagar *et al.* [10, 11] found that comparably simple morphologies [11] and controllers [10] were evolved across increasingly complex task environments, given a complexity cost. Such simple robots were more effective (fitter) overall compared to more complex robots evolved without a complexity cost. Similar results [32], found robot controllers and sensory configurations coevolved with a complexity cost were more efficient and effective (simpler and fitter), than those evolved without a complexity cost.

However, previous work [1] found more morphologically complex robots were evolved across increasingly complex task environments given a morphological complexity cost, thus supporting the *arrow of complexity* hypothesis positing that the complexity of organisms in open-ended evolutionary systems tend to increase in complexity over evolutionary time [3]. In most cases [1, 10, 11], multi-objective optimization was used as a complexity cost to concurrently minimize robot complexity and maximize fitness, where as others used approximations of *energy* costs proportional to robot complexity [15, 32]. Thus, the impact of varying environments and complexity costs on the evolution of body-brain complexity, remains unclear, as demonstrated by conflicting results reported across various evolutionary robotics studies [1, 9–11, 15, 32].

In this study we further examine the impact of increasingly complex task environments on evolving robot body-brain complexity given a complexity cost, where more complex body-brain designs are more expensive (in terms of lifetime energy consumption). This is motivated by biological hypotheses that evolved complexity incurs a cost, but enables greater pressure towards increased morphological complexity in more complex environments [8, 30]. We thus test body-brain evolution given the hypothesis that increasingly complex task environments coupled with a complexity cost, tends to induce selection for greater body-brain complexity, but not necessarily greater efficacy (fitness) across environments. The task was to evolve robot body-brain couplings best suited to maximize distance covered in various environments, where task complexity was increased by including obstacles, terrain friction and tilt [1, 19, 25].

To better elucidate relationships between environment and evolving complexity, we elaborate on evolutionary search techniques for coevolving body-brain complexity. Specifically, we test the efficacy of non-objective (*novelty* [21]) versus objective (*fitness function*) based search (section 2.3) for evolving robot body-brain couplings that effectively ambulate in given environments (section 3). Thus, a contribution of this study is its investigation of the relative efficacy of *non-objective* versus *objective-based* search to direct evolving

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body-brain complexity given a complexity cost and varying task environment complexity. Previous related work has only investigated environment and complexity cost impact on evolving body-brain complexity given a fitness function [1, 11, 15]. Others [27] have indicated the significance of sparse body-brain representations in the novelty search space to boost overall robot design efficacy.

2 METHODS

This section outlines body-brain (morphology-controller) representation, evolution methods and complexity metrics to evaluate evolved robot complexity. All methods were implemented using the *RoboGen* [2] open source framework and evolution simulation engine[1]. Methods extend those used by Jelisavcic *et al.* [19], for evolving robot body-brain design suited for adaptive locomotion.

2.1 Robot Body-Brain Representation

Body-brain representations used evolvable directed-graphs and indirect neural encodings for morphological control. Morphological representation (genotype encoding) was an evolvable directed-graph (Figure 1, center), where each graph-node represented a morphological brick (modular body-part) provided by *RoboGen* and the root node represented the core component (central body-part). Each graph-node could have up to four (4) children representing different body parts, where each node contained information about attached child nodes (modules) and module orientation. To simplify complexity calculation (section 2.6) and evolved morphological analysis, composite parts of robot morphology were limited to: *active-hinges*, *passive-hinges* and *fixed-bricks* and the *core component*[2], and maximum morphology tree size was 50 nodes.

Controller representation was an evolvable (HyperNEAT [35]) *Central Pattern Producing Network* (CPPN) [19] that encoded the weights of an associated substrate *Artificial Neural Network* (ANN), *brain*, where neurons comprising the ANN were distributed throughout the robot's morphology tree (Figure 1, right). To retrieve the connection weight between any two nodes in the ANN, coordinates of the corresponding morphology tree node (calculated relative to the core component) are used as CPPN query parameters.

Each morphological module could have multiple neurons attached (sub-controller), and each artificial neuron was a *Sigmoidal* or *Oscillator* unit [2]. Oscillators were attached to active or passive *joint* node (actuators), where a joint's range of motion was specified by the amplitude of the oscillator: [0, 1]. Morphological modules acted as *touch sensors* [2] or actuators (for example, Figure 1, center-right), and corresponded to ANN sensory inputs and motor outputs. Thus, the ANN represented the robot phenotype (elicited behavior) and the CPPN represented the genotype (behavioral encoding).

2.2 Body-Brain Coevolution

Body-brain coevolution used HyperNEAT [35] indirect encoding for evolving CPPNs (encoding ANN controller weights) and for executing sub-tree recombinations and mutation operations (applied by HyperNEAT [35]) for morphological evolution. Mutation operators were: *node removal*, *node addition*, *sub-tree removal*, *sub-tree addition.* Recombination operators were: *sub-tree duplication* and *swapping*. We used *deterministic tournament selection* and *elitist replacement* where only the least fit genotypes were replaced after applying parent selection, mutation and recombination operators. All genetic operators are described elsewhere [7] and presented in Table 1. To ensure initially functional robots, each body-brain encoding (genotype) was assigned a minimally-sized CPPN [34] and ANN substrate [35] initialised with random weights. Body-brain coevolution is summarised in the following algorithmic steps.

1. Randomly initialise n robot CPPNs and ANN weights.
2. Per robot ANN weights computed via CPPN querying.
3. Robot population evaluated in Q task trials (section 3)
4. All n robots assigned a *fitness* or *novelty* score (section
5. Until P offspring are created:
    (a) Deterministic tournament parent selection, where genetic operators applied to paired
6. Replace least fit P robots of population with offspring.
7. Enumerate steps 2–6 for N generations.

Experiments (section 3, Table 1) evaluated a *fitness function* (section 2.3) and *novelty search* (section 2.4) for robot body-brain design (genotype) task performance.

2.3 Fitness Evaluation

Given previous robot body-brain objective-based evolution [19], we evaluated the fitness of a given genotype (body-brain design) as the average *Euclidean* distance traversed by robots over Q simulation task trials (section 2.5) run per generation. Fitness was measured as the portion (normalized to the range: [0.0, 1.0]) of terrain length traversed (from far-left to far-right).

2.4 Novelty Evaluation

In line with previous work [21], after each task trial, novelty was calculated as the average *Euclidean distance* between a robot's end position and the end position of n nearest robots in the population and archive. After each generation, each new genotype was stochastically added to the novelty archive, up to the maximum archive size (Table 1). The archive was randomly composed and maintained (demonstrated as outperforming archives using high-novelty genotypes only [13]). Given that, x and y are normalized *behavioral characterization* vectors of two genotypes, the novelty of genotype x was quantified by Equation 1:

$$nov_x = \sum_{i=1}^{k} \delta_x(x, y_i) \tag{1}$$

Where, δ_x is the *Euclidean distance* between genotypes x and y, based on the behavioral characterization vector, x is the behavior of genotype x, and y_i is the behavior of the ith nearest neighbor of genotype x. The nov_x was derived from the mean of behavioral distance of an individual with k nearest neighbors. The parameter k is specified by the experimenter to represent the number of nearest neighbors, where $k = 15$ was used based on parameter tuning [13].

Behavioral characterization was the environment portion explored during robotic gait (normalized to: [0.0, 1.0], where 1.0 indicated all of the environment had been traversed). A low novelty score (Equation 1) thus indicated similar terrain ending positions and locomotive ability to previous robots. Whereas, a high novelty

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[1] RoboGen: robogen.org/

[2] http://robogen.org/docs/robot-body-parts/

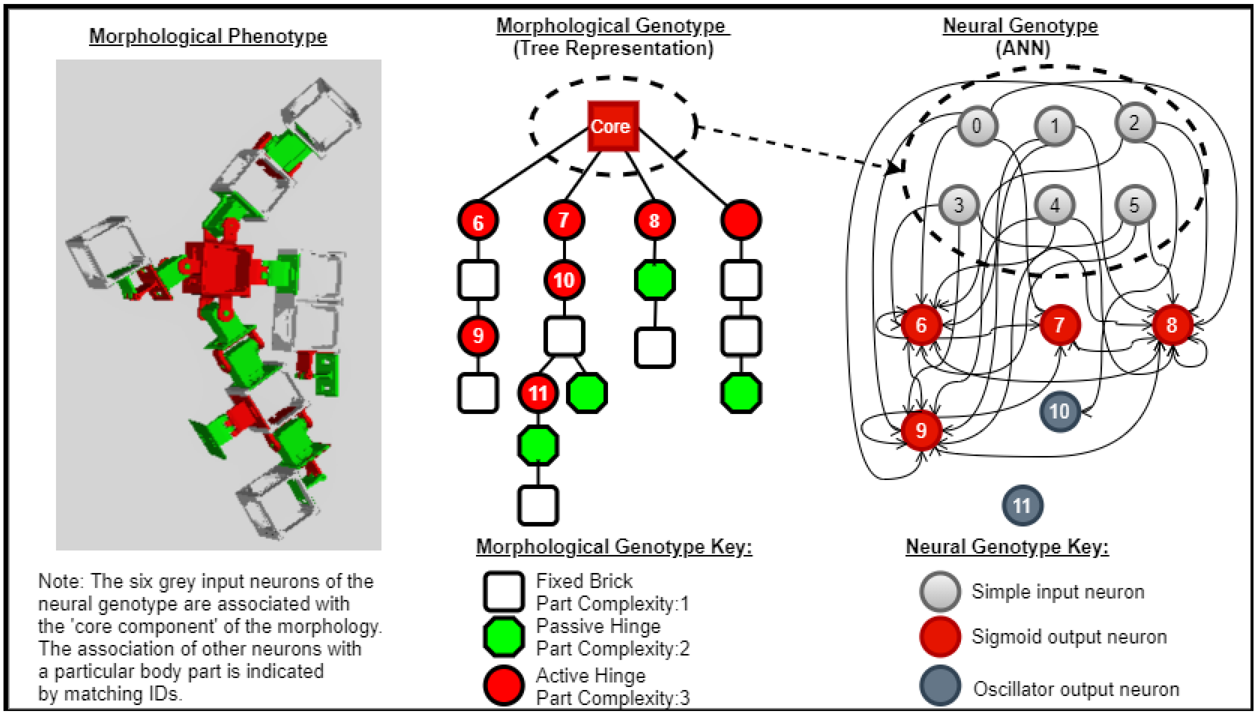

Figure 1: Example robot morphology (*left*) and (genotype) body-brain representation (*center, right*), indicating association between morphology (center) and controller neurons (*right*). Note: CPPN (section 2) controller representation is not shown.

score indicated new terrain ending positions and dissimilar body-brain designs. This novelty metric (measured over Q simulation task trials per generation) enabled evolving robots to maximize terrain explored, reaching sparsely populated regions of the genotypic (body-brain design) and phenotypic (gait behavior) search space.

2.5 Simulation Task Environments

Robots evolved body-brain designs, and thus gaits, suitable for maximising distance traversed and area explored on given terrains[3]. We tested 12 simulation environments of increasing complexity (environment sets 1–4, Table 2). As in previous work [24], adding obstacles and a titled terrain (*Terrain tilt*, Table 1) increased task difficulty (environment complexity). Varying terrain friction was present in all environments, where decreasing friction (1.0 to 0.2, Table 2), corresponded to increasing task difficulty, due to reduced traction making robot gaits overall less effective [1]. Environment set 1 was the *least complex* (flat, no obstacles and varying terrain friction). Environment set 4 was the *most complex* (titled and varying terrain friction). Whereas, environment sets 2 and 3 were of *medium complexity* (flat, obstacles and varying terrain friction). In environment set 2, small same-sized blocks were regularly placed with equal spacing between blocks and in environment set 3, varying sized blocks were irregularly placed with unequal spacing. Each task trial (*td*, Table 1), an evolved robot (section 3) was placed randomly in a *starting-area* on the environment's far left-hand side.

2.6 Complexity Cost

Given related work [15], evolving body-brain complexity cost was a function of the *energy cost* of controller and morphological complexity. Robot body-brain energy cost was realised as reduced task trial duration (*td*, Table 1), where more complex body-brain designs used more energy and this expense resulted in less body-brain evaluation time. Given a body-brain complexity value (*cs*, normalized to the range: [0.0, 1.0], where 1.0 indicated maximally complex designs), Equation 2 computed *adjusted task trial time* (*ad*).

$$ad = (1 - cs) * td \tag{2}$$

This energy-driven complexity cost was selected given demonstrated benefits [15, 16], as an evolving complexity cost tantamount to body-brain versus complexity trade-offs evident in natural evolution [30]. This complexity cost suitably represents dynamic relationships between evolving robot body-brain and environment complexity and robot task performance as it does not hinder exploration in evolutionary search via explicitly selecting for minimal complexity in evolving controllers [10] and morphologies [11].

Our complexity metric (Equation 3) accounts for morphological and neural complexity, where each is calculated and combined to give overall robot body-brain complexity. Robot body-brain complexity, *cs*, normalized to the range: [0.0, 1.0], quantifies overall morphological (*mc*, section 2.6.1) and controller (*nc*, section 2.6.2) complexity. A *cs* value close to 1.0 indicates a maximally complex robot (controller-morphology coupling), whereas a *cs* value close to 0.0 indicates a minimally complex robot.

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[3] The terms: *terrain*, *environment* and *task environment* are used interchangeably throughout and are tantamount to each other in this study.

$$cs = (0.7 * mc) + (0.3 * nc) \tag{3}$$

The motivation for 70% weighting for morphological complexity (mc) is that overall robot morphology is representative of robot controller complexity as morphological modules are integrated with the neural-controller (*active-hinge* modules correspond to ANN motor outputs and all modules correspond to ANN sensory inputs, section 2). Thus the higher the morphological complexity the higher controller complexity and the range of achievable behaviors [5].

2.6.1 *Morphological Complexity (mc).*

Is a function of number and type modules comprising robot morphology [1]. *Fixed-brick* was a passive (sensor) module and thus assigned a complexity of 1, whereas, the *passive* (joints) and *active* (motor-outputs) hinges were actuators contributing to morphological computation [28] and behavioral complexity thus assigned a complexity value of 2 and 3, respectively. Equation 4 specifies morphological complexity (mc) as the sum of module complexity for each morphological module.

$$mc = \sum_{n=1}^{t} c(n) \tag{4}$$

Where, t is the number of modules, $c(n)$ is complexity of module n, and mc is normalized to the range: [0.0, 1.0], using experimentally determined minimum (2) and maximum (90) morphological complexity (Table 1). The Figure 1 robot has the relatively low $mc = 0.35$, since this robot comprises only 15 of 50 modules (Table 1).

2.6.2 *Neural Complexity (nc).*

Calculates neural complexity via measuring *information integration*, defined as the amount of effective (shared) information transferable between neural sub-networks within a larger neural network [33, 36, 37]. This metric defines neural complexity as a trade-off between local specialisation and global integration (connectivity intensity and information exchange *within* and *between* sub-networks, respectively, where interactions between components at multiple network levels is an underlying principle of complexity [20]). Complexity is low in completely integrated or completely segregated systems and high where there is a balance between local specialisations and global integration.

Local specialisations are groupings of neurons (computational units) capable of producing isolated functionality since ANN outputs control *active-hinges* of the morphology. *Global integration* is the strength of connectivity between these computational units and represents varying *modularity* [4] that produces varying robot behavior (gaits) overall. For a given ANN (directed graph), complexity was a function of local specialisations (cycles within strongly connected sub-graphs representative of functional specialisation), and global integration (strength of connectivity between sub-graphs). Equation 5 calculated network specialisation, sp.

$$sp = (c/s) * (n/t) \tag{5}$$

Where, c is: number of *cycles*, s: *strong components* (local specialisations), n: neurons within strong components and t: total neurons in the network. All terms are defined in related work [36, 37]. *Global integration*, g, was the connectivity strength between strong components of the network, and computed as the ratio of connections between strong components to the number of strong components. Finally, neural complexity (nc) was calculated as the ratio of sp to g, where a higher sp versus g and higher g versus sp values indicate a higher versus lower neural complexity, respectively.

3 EXPERIMENTS

To ascertain the impact of *objective-based* (section 2.3) versus *novelty search* (section 2.4) to direct the evolution of body-brain complexity and associated task performance (fitness), two experiment sets were executed[4]. Experiments used either objective-based or novelty search and evaluated robot body-brain evolution in four (4) environment sets (12 environments of increasing complexity, Table 2), where each experiment measured average maximum task performance and associated body-brain complexity of evolved robots. All experiments were run using the *Robogen*[5] open-source modular robot evolution engine and physics simulator [2].

Each experiment comprised 20 runs, where each run was 100 generations and each generation 10 simulation task trails. Each task trial was 10 seconds in duration (Table 1), and initialised a random starting position of an initial robot design (in a starting area on the far left-side of the environment). For environment sets 2 and 3 (Table 2), task trials initialised obstacles at random positions in the environment. Per task trial, task performance was the portion (normalized to the range: [0.0, 1.0]) of the total environment (from far-left to far-right) traversed by robots. Task performance was averaged over 10 task trials (per generation). Robots yielding the average maximum task performance were selected after 100 generations (per run). Average maximum task performance was calculated over 10 runs, where complexity of the highest task performance robot evolved per run was selected. Average complexity was then calculated as the average over 20 runs.

Experiments 1 and 2 thus evaluated average maximum task performance and complexity of robots evolved by objective-based versus novelty search, respectively, over increasingly complex task environments (Table 2). All experiments started with an initial population of 100 randomly initialised robot body-brain couplings (section 2.2), and included an energy cost on evolving complexity (section 2.6). Robots were evolved for the purpose of adapting gaits suitable for given environments (ambulating as far as possible across a terrain in a 10 second simulation task trial). Experimental, simulation and evolution parameters are summarised in Table 1.

4 RESULTS AND DISCUSSION

Experiments applied *objective* (section 2.3) versus *novelty* (section 2.4) based evolutionary search to evolve robot body-brain designs in increasingly complex task environments (Table 1). Experiments computed average maximum *task performance* (fitness) and associated average *maximum complexity*, of robots evolved over 20 runs.

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[4] Experiment source code, method parameter sets and videos of evolved robots available at: https://github.com/BrookeSte/EVOBAB

[5] Robogen: http://robogen.org/, was run on an Ubuntu Virtual Machine: 8 Intel(R) Xeon(R) Gold 6254 CPUs @ 3.10GHz. 32GB RAM.

Experiment Parameters	
Experiment	Novelty search or Fitness function
Runs	20
Simulation task trials	10
Task trial duration (*td*)	10 seconds (section 3)
Terrain tilt	15 degree incline
Task Environments : Terrain Friction	(1, 4, 7 , 10) : 1.0 , (2 ,5, 8, 11) : 0.6 , (3, 6, 9, 12) : 0.2
Body-Brain Coevolution Algorithm Parameters	
Seed Robot Population	True (Initial seed *Robogen* robot configuration [2])
Minimum | Maximum morphological complexity per robot	(2: 1 module) | (90: 50 modules)
Population Size | Generations	100
Parent Selection	Deterministic Tournament Selection (k=2)
μ Parents | λ Offspring	100 | 50
Mutation | Recombination Probability (All operators)	0.3 | 0.1
Probability of Addition (Novelty Archive)	0.3
Replacement Strategy	Plus replacement [7]
Novelty Archive Size | Nearest Neighbors	50 | 15

Table 1: Experiment and Evolutionary Parameters

	Environment	**Friction**	**Obstacles**	**Tilted**
Set 1	1	1.0	None	No
	2	0.6	None	No
	3	0.2	None	No
Set 2	4	1.0	Regular	No
	5	0.6	Regular	No
	6	0.2	Regular	No
Set 3	7	1.0	Irregular	No
	8	0.6	Irregular	No
	9	0.2	Irregular	No
Set 4	10	1.0	None	Yes
	11	0.6	None	Yes
	12	0.2	None	Yes

Environment Number	**Average Task Performance**	**Average Complexity**
1	***NS*** > ***OS*** ($p < 0.05$)	NS == OS ($p \geq 0.05$)
2	***NS*** > ***OS*** ($p < 0.05$)	NS == OS ($p \geq 0.05$)
3	***NS*** > ***OS*** ($p < 0.05$)	NS == OS ($p \geq 0.05$)
4	***NS*** > ***OS*** ($p < 0.05$)	***NS*** > ***OS*** ($p < 0.05$)
5	***NS*** > ***OS*** ($p < 0.05$)	***NS*** > ***OS*** ($p < 0.05$)
6	***NS*** > ***OS*** ($p < 0.05$)	***NS*** > ***OS*** ($p < 0.05$)
7	***NS*** > ***OS*** ($p < 0.05$)	***NS*** > ***OS*** ($p < 0.05$)
8	***NS*** > ***OS*** ($p < 0.05$)	***NS*** > ***OS*** ($p < 0.05$)
9	***NS*** > ***OS*** ($p < 0.05$)	***NS*** > ***OS*** ($p < 0.05$)
10	***NS*** > ***OS*** ($p < 0.05$)	NS == OS ($p \geq 0.05$)
11	***NS*** > ***OS*** ($p < 0.05$)	NS == OS ($p \geq 0.05$)
12	***NS*** > ***OS*** ($p < 0.05$)	NS == OS ($p \geq 0.05$)

Table 2: *LEFT:* Environment parameters per set. Each environment per set had differing friction but utilised the same obstacle set or a tilted floor. *Regular* obstacle sets contain obstacles that are regularly spaced from one another whilst *irregular* sets contain obstacles that are irregularly spaced. A *Tilted* value of *Yes* indicates that the environment floor was tilted at an incline. *RIGHT:* Statistical comparisons (Mann-Whitney U-tests [23]) between average task performance and average complexity results for robots evolved by *Novelty Search* (NS) versus *Objective-based Search* (OS), where task performance averages are calculated using maximum task performance selected from each run (averaged over 20 runs for a given experiment), and average complexity (20 runs) is that associated with robots yielding the maximum task performance (selected from each run).

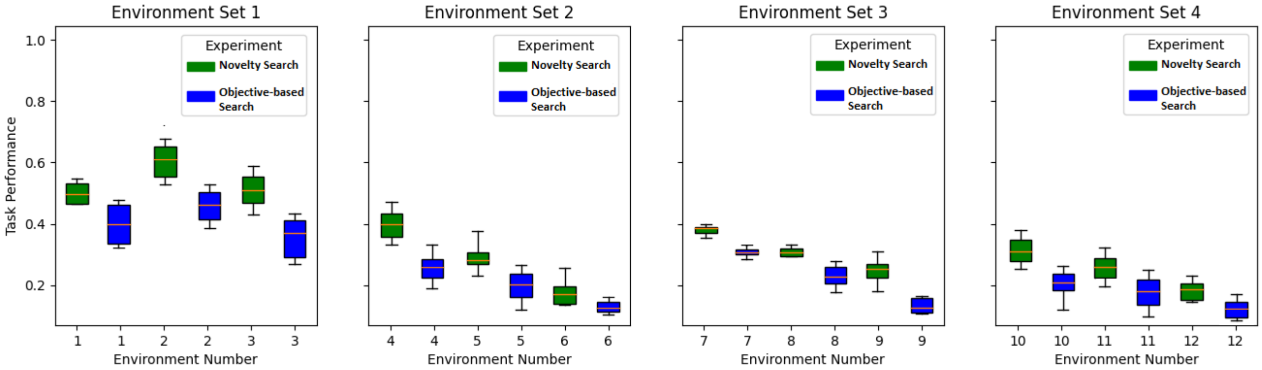

Figure 2: Average maximum *task performance*: robots evolved per environment set (Table 1): *objective-based, novelty search*.

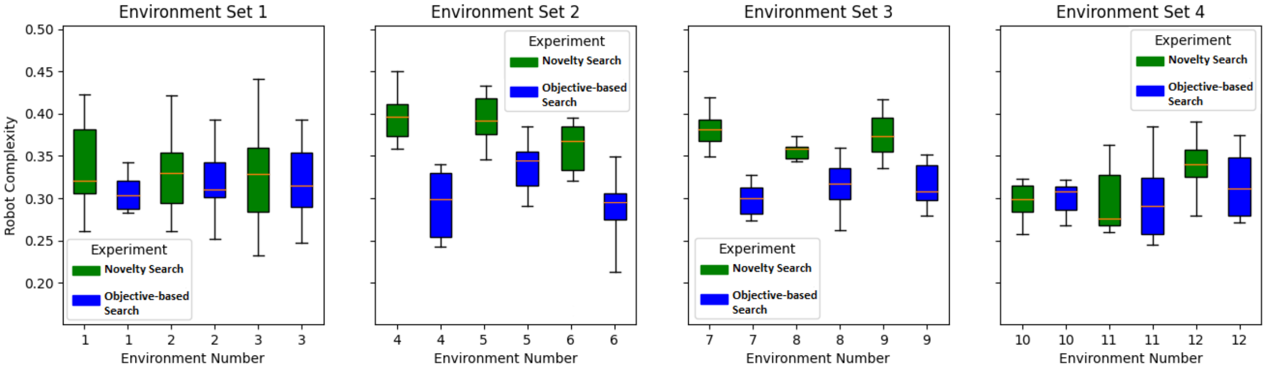

Figure 3: Average maximum *body-brain complexity* (and maximum task performance): robots evolved per environment set.

We applied the *Mann-Whitney U* test [23] (p<0.05) to test for statistically significance in pair-wise results comparisons, where *Levene’s test* [22] was applied *a priori* to ensure assumed equal variances as required by the Mann-Whitney U test. Statistical comparison results are summarised in Table 2, where average maximum task performance was calculated via selecting the evolved robot body-brain design with the highest task performance from each run, and calculating the average over 20 runs. The average maximum complexity was calculated via selecting the complexity corresponding to the highest task performance robot (per run), and calculating average maximum complexity over 20 runs.

Average maximum task performance comparisons indicated that for all environment sets (environments 1–12, Table 2), *novelty search* evolved robots significantly out-performed those evolved by objective-based search (Figure 2, Table 2: *right*), indicating the benefits of novelty search (comparative to objective-based search), for evolving robot body-brain designs that are consistently effective across task environments. Notably, in environment sets 2 and 3, accompanying higher average task performance, novelty search also evolved significantly more complex body-brain designs (Figure 3, Table 2: *right*). To gauge environment impact on evolving complexity, given *novelty* versus *objective-based search* body-brain evolution, we also applied *Mann-Whitney U* (p<0.05) to test for statistical difference between body-brain complexity of the fittest robots evolved per environment set (Figure 3). Statistical comparisons indicated robots evolved in environment sets 2 and 3 (defined by obstacles and varying degrees of traction, Table 2), had significantly higher complexity compared to robots evolved in environments with no obstacles or with terrain tilt (sets 1 and 4, Table 2).

Significantly higher body-brain complexity was evolved for the fittest robots in environments containing obstacles and varying terrain friction. This is supported by previous work [24] similarly demonstrating that varying environment conditions, such as the presence of obstacles and terrain tilt, results in the evolution of significant differences in morphological and behavioral design, without a clear correlation between increasing task environment complexity, average fitness (distance covered by evolved robotic gaits), and types of morphologies evolved (and thus gaits produced). Here, only *novelty search* (Figure 3) evolved significantly more complex body-brain designs. Robots evolved by objective-based search had comparable average fitness and associated complexity per environment set (Figures 2 and 3).

These results indicate that specific environment conditions, including varying terrain friction in conjunction obstacles (regularly placed small-sized blocks and irregularly placed varying-sized blocks), provided the environment conditions for novelty search to evolve more complex body-brain designs. This increased body-brain complexity was beneficial, as it yielded an accompanying significantly higher task performance compared to robots evolved by objective-based search (environment sets 2 and 3, Figure 2). In support of this, robot complexity evolved by novelty search in environments without obstacles (environment sets 1 and 4), yielded a significantly lower body-brain complexity compared to those evolved environment sets 1 and 2 (*Mann-Whitney U, p*<0.05).

Overall, results indicate that given suitable environment conditions (evidenced in environment sets 2 and 3), *novelty search* enables the evolution of high complexity body-brain designs yielding an accompanied high task performance. This was in comparison to average task performance (Figure 2) and complexity (Figure 3) of robots evolved by objective-based search in these same environments. However, task performance and complexity results also elucidated that without specific environment conditions (obstacles), novelty search still evolved more effective (fitter) robots but with (statistically) comparable complexity to robots evolved by objective-based search in the same environments (environment sets 1 and 4, Figures 2 and 3). That is, despite lower complexity robots evolved by novelty search in environment sets 1 and 4 (compared to sets 2 and 3), these body-brain designs still yielded a significantly higher task performance compared to robots evolved by objective-based search (fitness function optimising for distance travelled) in the same environment sets (1 and 4). This is supported by previous work [29], similarly demonstrating added complexity is often a hindrance to achieving higher task performance given specific task environment conditions and constraints.

Thus, body-brain exploration (novelty search in this case), was able to take advantage of specific environment conditions (obstacles and varying terrain friction in environment set 2 and 3, Table 2), to evolve more complex and high task performance body-brain designs. However, when these specific environment conditions are not present (no obstacles, varying terrain friction and tilt in environment sets 1 and 4, Table 2), then novelty-search evolves less complex, but high task performance body-brain designs. Related work [26, 27], similarly demonstrates novelty search as suitable for evolving diverse body-brain designs with potential effective functionality across various types of task environments.

These results indicate the importance of an appropriate evolutionary (robot design) search for producing robots with body-brain complexities that enable (task accomplishing) behaviors suitable for varying task environment conditions, and not necessarily increased body-brain complexity concomitant with increased task environment complexity [1]. We conclude that non-objective based evolutionary search given varying task environment conditions (environment complexity), facilitates the evolution of suitably complex and effective body-brain robot designs. Notably, these results are supported by related evolutionary robotics studies independently demonstrating that evolved controller [10] and morphological [11] complexity as well as coevolved body-brain couplings [9] is heavily dependent on task and environment constraints.

This study's key contribution was elucidating the value of body-brain exploration (novelty-search) for directing the evolutionary search for robot body-brain designs given specific task environment conditions. In this study, these conditions were obstacles and varying terrain friction. Body-brain evolution, using objective-based (fitness function) search running in these same environments produced a significantly lower body-brain complexity and task performance indicating that the exploratory search process of novelty-search conferred specific advantages in these environments.

Ongoing research is investigating comparative body-brain and environment complexity metrics to further evaluate the impact of the environment on evolving robot body-brain designs and thus elucidate the conditions under which low versus high body-brain complexity is necessary for survival (high task performance in evolutionary robotics studies). Also, the relatively poor performance of objective-based search overall was likely due to strong selection and convergence to sub-optima. We are thus investigating the use of alternative selection mechanisms with genotypic diversity maintenance such as *crowding* [12], as well as the impact of hybrid objective-novelty selection in evolutionary search [13].

5 CONCLUSIONS

This study investigated the impact of novelty versus objective-based body-brain evolutionary search for adapting robot body-brain (controller-morphology) designs given increasingly complex task environments. Results elucidated that novelty search evolved robot body-brain designs consistently out-performed (average environment distance traversed), objective-based evolved robots. Results also indicated that novelty search, compared to objective-based search, enabled the evolution of increased body-brain complexity (concomitant with increased task performance) given specific environment conditions. These results contrasted to previous related work supporting the *arrow of complexity* hypothesis. In this study, increased task environment complexity did not induce the selection of an accompanied increase in robot body-brain complexity. Rather, environments containing obstacles and varying terrain friction, enabled novelty-search to evolve significantly more complex and effective (higher task performance) robots. This study's key contribution was the demonstrated efficacy of body-brain explorative search (novelty search) for evolving robot complexity necessary to yield high task performance in specific environments. The efficacy of such body-brain exploration was supported by the comparatively low complexity and task performance of robots evolved by objective-based search in these same environments.

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