Automating Robot Design with Multi-Level Evolution

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***Abstract*—In evolutionary robotics, *Multi-Level Evolution* (MLE) has been demonstrated for effective robot designs using a bottom-up approach, first evolving which materials to use for modular components and then how these components are connected into a functional robot design. This paper evaluates MLE robotic design, as an evolutionary design method on various task (robot ambulation) environments in comparison to human designed robots (pre-designed robot controller-morphology couplings). Results indicate that the MLE method evolves robots that are effective across increasingly difficult (locomotion) task environments, out-performing pre-designed robots, and thus provide further support for the efficacy of MLE as an evolutionary robotic design method. Furthermore, results indicate the MLE method enables the evolution of suitable robotic designs for various environments, where such designs would be non-intuitive and unlikely in conventional robotic design.**

***Index Terms*—Evolutionary Robotics, Multi-Level Evolution.**

I. Introduction

One proposed solution for solving critical societal challenges is the commercialization of autonomous robots [1] that can be rapidly and economically designed, produced, and deployed *on-demand* [2]. However, current robots are still not widely used in applications such as agriculture, environmental cleanup, civil infrastructure maintenance, and natural disaster management [3]. The core problem is that such applications are too varied, too dynamic, and too complex for economically viable pre-engineered robot designs. As such, even state-of-the-art robots such as Mars rovers are still directed by human operators [4]. Another limitation is that current robot morphologies (sensory-motor hardware) and controllers (control software) must be re-engineered for every new application. Current robots are also fragile meaning any change in task environment or hardware and software failures requires engineering teams to reconfigure hardware, software or even scrap robots. This greatly limits what societal challenges autonomous robots can help us solve.

This paper presents research extending and contributing to automated evolutionary robot design methods. The *Multi Level Evolution* (MLE) framework [5], [6] has been proposed as one such method. MLE is a bottom-up multi-layered evolutionary design framework that enables the generation of novel robot designs via first evolving materials to comprise robot components (material level), then evolving the types of components to comprise the robot morphology (component level), and finally evolves the composition and interaction of components as a complete body-plan (morphology level).

The exploration versus exploitation trade-off of the MLE optimization process is based on quality-diversity methods [7], where solutions are discovered via exploring various feature dimensions. In this case study, this feature space is defined by a range of material values (defining material type), modular component geometries (defining robot building blocks), and robot morphologies (defining in complete robot designs). The main benefit of MLE is its multi-level bottom-up approach enables the discovery of a vast range of robot designs by virtue of solutions optimised at each level comprise re-usable solutions optimised at the level below. That is, evolved robot morphologies comprise evolved modular components which in turn comprise evolved material properties, where evolved solutions are re-used by the upper levels. A second benefit is that MLE is scalable to a higher number of features per level since MLE evolutionary search concurrently and independently operates on each level [5], [6].

Designing optimal robots for unknown task environments is difficult given innumerable non-trivial interactions between morphology and controller. However, evolutionary robotics [8] is an ideal experimental platform for investigating various controller-morphology (body-brain) optimization methods in company with robotic simulators or even physical robots [9]. A key benefit of evolutionary robotics is that it supports the robot design process, removing design bias of human engineers, while exploring a body-brain design space, leading to non-intuitive, unconventional yet near optimal designs [10]. However, due to the intractable computational complexity of the body-brain design search space, for all but the simplest robot designs, the scope of body-brain artificial evolution is typically limited, for example, adapting neural controller connection weights in concert with switching sensors on and off [11], [12]. This is especially problematic if we intend to evolve robot designs for complex tasks in unknown environments [2], since highly constrained morphologies greatly limits the complexity of possible behaviors [13]. MLE is proposed as a potential solution, since it is a means to search a vast space of possible designs, enabled via the bottom-up level approach, where suitable materials and components evolved at lower levels are re-used at the higher level of optimising complete robot designs. Thus the MLE bottom-up, multi-level design approach is hypothesized to be more efficient compared to current evolutionary robotic body-brain design approaches, where functional robot designs generated by MLE can also be more complex resulting in a broader range of possible behaviors, meaning that overall MLE can evolve robot designs suitable for a broader range of task environments.

MLE uses *Quality Diversity* (QD) to balance exploitation versus exploration of vast solution spaces (indicative of, for example, robot body-brain design). QD methods [7] use specially designed evolutionary optimization via maintaining maps of high quality (high task performance solutions) but diverse solutions, and have received significant attention in evolutionary robotics. Specifically, such QD methods have been demonstrated as an effectively maintaining controller (brain) and morphological (body) diversity during evolutionary optimization of robot designs in varying environments. For example, QD methods have co-evolved the controller-morphology (body-brain) designs of soft robots moving to goal areas via deforming their shape [14], robots that effectively ambulate across increasingly difficult gait adaptation tasks [15]–[17], as well as robots designed for more complex tasks such as reconnaissance and gathering [18]–[20]. This study's primary objective is thus to extend previous work on MLE legged robot design [6], providing further evidence supporting the efficacy of MLE for evolutionary robotic design.

Evolutionary robotics has also been used as an experimental platform to address questions about the evolution of morphological complexity given increasing environment complexity (task difficulty) [12], [20], [21]. Other work [21] demonstrated the evolution of increasing morphological complexity given robot morphology-behavior (body-brain) adaptation to ambulate across increasingly difficult terrains. Related work on co-evolving body-brain complexity of robots using novelty-search [22], over increasingly complex terrains with specific environment features such as obstacles [23], enabled the evolution of robots with high task-performance and high body-brain complexity. However, experiments evaluating evolving morphological complexity for increasingly complex collective gathering tasks indicated that robots with simpler morphologies yielded task-performances comparable to those with more complex morphologies [12], [20].

Given such conflicting experimental evidence on evolving morphological complexity given increasing environment complexity, our secondary objective is to further elucidate the impact of environment complexity (task difficulty) on evolving robot morphological complexity. This objective is also relevant from the practical perspective of robot design. That is, it is desirable to keep robot design as cheap and effective as possible whilst enabling optimal or near-optimal behaviors. Thus if evolutionary robot design methods can generate minimal but effective robot morphologies for given simulated task environments, then this would benefit the engineering of counter-part physical robotic systems.

Overall, this study presents results of MLE applied to evolve robots over increasingly difficult task environments, where evolved robot designs are compared to pre-designed robots. Results contribute to the larger objective of *AutoFac* methods [2] for automating robotic systems tailor designed for optimal operation in specific environments. Such *AutoFac* methods would enable automated robot design for applications without optimal and economical robotic solutions. Example applications include automated environmental cleanup, natural disaster management and search and rescue operations [1].

II. Methods

This section overviews the *Multi-Level Evolution* (MLE) method used for robot behavior-morphology evolution in this study (section III). MLE uses CVT-MAP-Elites [24] for multi-level evolutionary design. The bottom level is the materials level (comprising materials with pre-generated properties), next is the components level (combining point-based shape grammars to generate robot legs), and last is the robot level (combines legs into complete functional morphologies). Algorithm 1 presents an overview of the MLE pseudo-code, however the MLE method is fully described in previous work [6], so here we present a summarized version only.

A. Material, Component and Robot Representation

At the material level, material types are represented as combinations of *friction* and *restitution* coefficient values [25], constrained to the range: [0.25, 0.50, 0.75, 1.0], resulting in 16 material types. At the component level, sets of connected components (robot legs) are represented as shape grammars [26], [27], where individual component shapes (irregular polygons) are represented as point clouds [28] with an associated material type. At the robot level, morphologies are represented as a rectangular torso (component length: [1, 8, 16]), connecting [2, 4, 6] legs, where minimum and maximum torso length corresponds to the minimum and maximum number of legs.

B. Material, Component and Robot Evolution

Map-Elites [24] (Algorithm 1) was applied to evolve both components (comprising robot legs) and robot morphologies (how legs were connected to the robot torso), where four features at the component level and three features at the robot level (table I), ensured that morphological diversity was maintained in the evolutionary selection of components and subsequent morphologies comprising evolved components.

Material types were evolved via selecting combinations of *friction* and *restitution* values to associate with components, and subsequently selecting varying component shapes, where

Algorithm 1 Multi-Level Evolution (MLE) Method [6]

Input: MLE and environment parameters P; Materials M; Components C; MAP-Elites(P,M); MAP-Elites(P,C)

Output: Optimized robot design r (behavior-morphology)

```
for i = 1, ..., N (Generations) do
    C ← MAP-Elites(P, M)
    R ← MAP-Elites(P, C)
end for
return Fittest robot (r)
```

such components (evolved shapes) are connected together by an evolved grammar (forming a complete leg). At the component layer, components and how components are connected (to form legs) are mutated using one of four (randomly selected per generation) component mutation operators (table I). Similarly, at the robot level, one of four mutation operators (randomly selected per generation) are used to adapt leg actuation (joint movement-types: *fixed* or *revolute* (Leg can move in robot's forward-backward or upwards-downwards axis) between each leg component) and the number of legs (table I). An evolved number of (pairs) of evolved legs are attached to the robot torso (applied symmetrically), to form a complete robot morphology. The component level fitness function averages the volume to surface area ratio across all components comprising a leg, selecting for evolved leg shapes that are compact, by maintaining an appropriate proportion between volume and surface area. The robot level fitness function was defined as the portion of an environment's length (normalized to: [0.0, 1.0]) that an evolved robot traversed in a task trial (table I).

C. Robot Controller Evolution

Multiple (N) controllers actuated N joints connecting all leg components, where controller output was the change in joint position for joint j (at time step t), where N depended upon the number of components (in each leg), and each controller was defined by a sinusoidal wave actuation [6]. All controller variables (*amplitude*, *frequency*, *phase*, and *offset*), normalized to: [-1.0, 1.0], were optimized using a 1 + 1 EA [29], where the number of variables depended on the number of components and non-fixed joints. The evolution of all controller parameters and the interaction of all component controllers thus determined a robot's overall (gait) behavior.

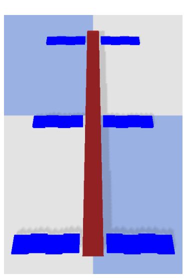

Fig. 1. Pre-designed robot morphology as per related work [6], using material type: *friction*, *restitution* = (0.75, 0.75), indicated by blue legs).

TABLE I
SIMULATION AND EXPERIMENT PARAMETERS

Parameter	**Value**
MAP-Elites	
Generations (Both levels)	1000
Component level features	Mean component *friction* *restitution*, leg size leg complexity [6]
Robot level features	Mean leg *friction* *restitution*, leg size
Niches	1000
Initial proportion of filled niches	0.1
Simulation Environment	
Starting points (On starting line)	5 (random)
Surfaces (flat, incline)	0°, 15°
Task trial (duration)	15 seconds
Ground friction (low, high)	0.05, 0.9
Robot Morphology	
Component mutation operators	Shape, Connection rule Torso connection shape Material type
Robot mutation operators	Replace leg, Joint-type Number of legs Controller only evolution
Torso (constituent blocks) size	[1, 8, 16]
Leg maximum length	24 (2 legs)
Leg number range	[2, 4, 6]
Leg component size range	[0.01, 0.16]
Maximum components per robot	64
Joint upper limit (radians)	0.2
Joint lower limit (radians)	-0.2
Joint delta movement (radians)	[-0.05, 0.05]
Controller Evolution: 1 + 1 EA	
Task trials (per generation)	5
Runs (1000 generations)	10

D. Pre-Designed Robots

To demonstrate the efficacy of MLE evolved robots across various task environments (section III) we evaluate a set of 16 pre-designed robots, where each of the 16 is denoted by a specific property type. That is, specific values (property types) derived from each discrete value combination for the coefficient of *friction* and *restitution* properties (section II-A). Figure 1 presents the (hexapod) morphology of the pre-designed robot, selected given its use in previous relevant experiments [6], where the key difference is previous work only tested one property type (friction = 0.75, restitution = 0.75, blue components in figure 1), whereas we evaluated 16 material types.

As in previous work, each leg comprised four square polygons, each with friction and restitution coefficients of 0.75. In the context of the robot simulator [6], the robot torso is 0.16 units in length, each leg component block is 0.01 units in length. For comparison, maximum task-performance (1.0) is gained if a robot traverses 1.0 unit in any given environment (section III).

E. Morphological Complexity Definition

We define *morphological complexity* [12], as a function of the number of modular robot building blocks (components), number of legs and number of components per leg. Component material composition was not factored into this calculation given a lack of universal material complexity classification metrics [30], [31], especially in robotics [32]. Robot morphological complexity (M, equation 1) is defined as the given number of legs N, where each leg l_i comprises a number of blocks out of a maximum number of blocks L (that could comprise any robot). The maximum number of blocks (L) per robot (table I) was determined by trial simulations using pre-designed robots (section II), testing varying numbers of legs and leg lengths, and gauging task-performance across the same environments as used for MLE experiments (table II). This maximum value (L=54, table I), was the maximum number of components used by functional (ambulating) robots evolved for all environments (section III). To limit the morphological search space to functional robot designs, MLE evolved morphologies were constrained to [2, 4, 6] legs, where minimum robot complexity was two legs (one component each and one torso component), and maximum complexity was six legs (each comprising eight blocks and 16 torso components).

$$M = \sum_{i=1}^{n} \left(\frac{l_i - \wedge L_i}{\vee L_i - \wedge L_i} \right) \tag{1}$$

Where, n is the number of legs ($n \in [0, N]$) and the complexity of composite leg i (l_i) is defined as:

$\frac{l_i - \wedge L_i}{\vee L_i - \wedge L_i}$: Fraction of total possible blocks used by l_i.

III. Experiments

Experiments ran on custom robot simulator [33] using MLE [6] to evolve legged robot designs suitable for various environments (table II). Task environments (A-D, table II) used in these experiments are ordered in terms of increasing difficulty. Surface friction of 0.90 indicated maximum traction, so coupled with a flat surface, was the least difficult environment to traverse (*simple*, table II). However, 0.05 indicated relatively low traction, so coupled with an inclined surface this was the most difficult environment to traverse (*difficult*, table II). Robot task-performance was evaluated as the portion of the environment length covered during one task trial (15 seconds, table I). We conducted four sets of *evolutionary* and subsequently evaluation experiments.

Each evolutionary experiment ran for 1000 generations, evaluating a population of 100 robot designs per environment. Per generation, each robot was evaluated by gauging the average portion of environment length traversed over five *task trials* (15 seconds each). If during any task-trial, robots moved beyond a given side-lines boundary or changed orientation to a non-forward moving direction, the simulation was stopped and the robot assigned a 0 fitness. Per generation, after all robots had been evaluated, evolutionary operators were applied to generate the next generation of robot designs. Average task performance was calculated over 10 runs using the fittest (highest task-performance) evolved robot per run.

The evaluation experiments entailed testing the fittest MLE robot evolved for each environment versus a robot *pre-designed* (section II-D) for the same environment. To address our objective (section I) of demonstrating MLE efficacy for generating effective robot designs across environments, we evaluated evolved designs versus various pre-designed robots. First, versus the pre-designed hexapod morphology with a constant material type per component (friction=0.75, restitution=0.75) taken from previous work [6]. Second, versus the best performing of 16 pre-designed hexapod morphologies [6], where each pre-designed robot used one of 16 different material types (section II). Specifically, each evaluation run took, for a given task environment, the fittest MLE evolved robot after 10 evolutionary runs. This fittest evolved robot was then evaluated versus the original pre-designed robot [6], or the pre-designed robot (using one of the 16 material types, section II) in a simulation task trial of 15 seconds (table I), replicating each of the four task environments (table II). These task trials were only used to evaluate robot ambulation task-performance and as such no evolutionary adaptation occurred during each task trial.

To ensure statistical viability of robot task-performance comparisons, for each task trial (replicating one of the four task environments), we ran 10 repetitions for the fittest MLE evolved robot versus one of the 16 pre-designed robots. For each task trial run, robots started in random locations (on a starting line spanning the width of the environment), and an average task-performance was computed over the 10 task trial repetitions for evolved versus pre-designed robots (section IV). Table I presents all MLE and experiment parameters used in this study, and unless otherwise described, parameter values are the same as that used in related work [6] (where a complete list of MLE and simulation parameters is available). All experiment simulations were implemented in Python using the custom robot simulator and MLE engine [6], and executed on a HPC cluster (2, 10, 25 nodes) comprising Intel Xeon 24 core CPUs running at 2.6GHz with 64GB of RAM. Experiment implementation, testing and parameter tuning was executed on an AMD Ryzen 9 5950X 16 core CPU running at 4.9GHz with 32GB RAM and Nvidia 3080 Ti 12GB GPU.

IV. Results and Discussion

A. Evolved Gait Performance and Morphological Complexity

To address our first research objective (section I), we first examine comparative average task performances of MLE robots evolved per environment and the highest task performance of 16 pre-designed robots (section II) and the four best performing robots with various pre-defined materials, for the pre-designed robot morphology (section III), in the same environments. Pair-wise statistical tests applied between

TABLE II

ENVIRONMENTS AND ASSOCIATED TASK DIFFICULTY. AS PER PREVIOUS WORK [6] SURFACE FRICTION OF 0.90 INDICATES MAXIMUM TRACTION DURING ROBOT AMBULATION. COUPLED WITH A FLAT SURFACE, THIS IS THE LOWEST TASK DIFFICULTY (SIMPLE ENVIRONMENT). WHEREAS: 0.05 INDICATES LOW TRACTION, COUPLED WITH AN INCLINED SURFACE THIS IS THE HIGHEST TASK DIFFICULTY (DIFFICULT ENVIRONMENT).

Task Environment	Environment Type	Task Difficulty	Surface Friction
A	Flat	Simple	0.90
B	Flat	Medium-low	0.05
C	Inclined (15°)	Medium-high	0.90
D	Inclined (15°)	Difficult	0.05

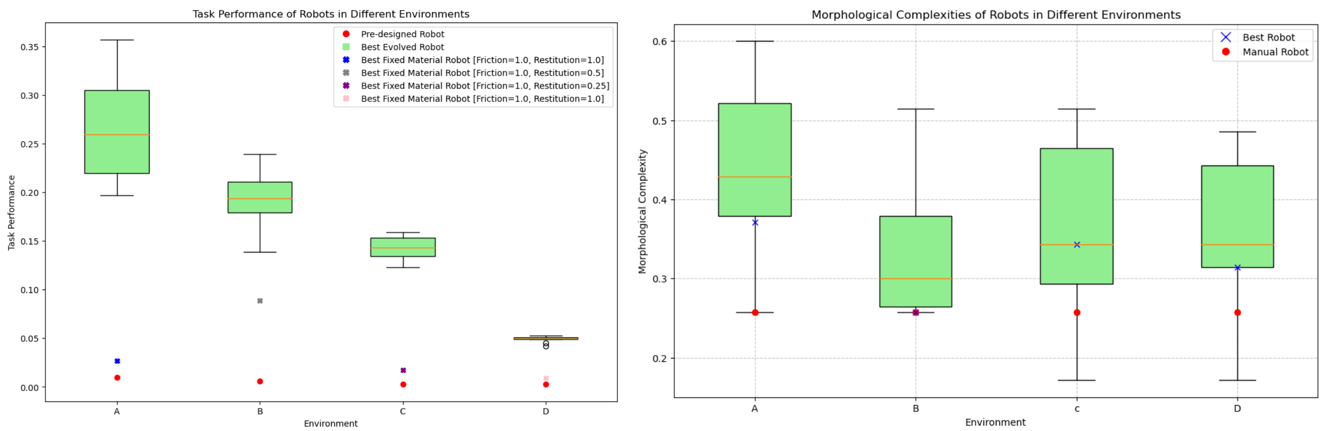

Fig. 2. **LEFT:** Average maximum task-performance of evolved (box-plots) versus pre-designed robots per environment (red dot, colored stars in legend). Note, the pre-designed robots did not evolve morphology-behavior, so there was minimal variation in gait behavior. **RIGHT:** Morphological complexity of the highest task-performance robots evolved in each task environment. For each environment, *Best Robot* corresponds to those visualized in figure 3). *Manual Robot* is the pre-designed robot (section II-D). Morphological complexity is normalized to: [0.0, 1.0], where 0.05 and 1.0 indicate the simplest and most complex possible robot (section II-E), respectively. **A:** High friction, **B:** Low friction, flat surfaces (environments A, B: table II), **C:** High friction, **D:** Low friction inclined (15°) surfaces (environments C, D: table II). Fitness (normalized) is the distance traversed (as portion of environment length).

TABLE III

EVOLVED MORPHOLOGICAL COMPLEXITY AND MATERIAL TYPES (FRICTION AND RESTITUTION VALUES) OF FITTEST (HIGHEST TASK-PERFORMANCE) ROBOT EVOLVED (FIGURE 3) IN EACH TASK ENVIRONMENT (TABLE II)

Environment	Morphological Complexity	Materials (Friction, Restitution)
A	0.38	Yellow (1.0, 0.75), Green (0.25, 0.25), Blue (0.75, 0.5)
B	0.27	Yellow (1.0, 0.75), Green (0.25, 0.25), Blue (0.75, 0.5)
C	0.34	Yellow (1.0, 0.75), Green (0.25, 0.25), Red (0.5, 0.25)
D	0.31	Yellow (1.0, 0.75), Green (0.25, 0.25), Blue (0.75, 0.5), Red (0.5, 0.25)

the average task performance results of MLE evolved versus the pre-designed robot (section III) indicate MLE evolved robots achieve a significantly higher average task performance ($p<0.05$) across all environments (figure 2, left). Results data were non-parametric, found via a Kolmogorov–Smirnov normality test with *Lilliefors* correction [34]. Mann–Whitney U tests ($p<0.05$) [35] were applied in pair-wise comparisons with Effect Size [36] treatment (all statistical test results are online [33]). For our second objective (section I), to demonstrate morphological impact in MLE evolved robots, we examine the morphological complexity (section II-E) of MLE evolved robots. For comparison we compare morphological complexity of the fittest robot evolved per environment with the morphological complexity of the pre-designed robot [6].

Table III presents the morphological complexity (section II-E) computed for the fittest (highest task-performance) robot evolved in each environment (table II) and figure 2 (right) presents the average morphological complexity of the fittest robots evolved per environment. Statistical tests indicate that the average morphological complexity of the fittest robots evolved for environments B, C and D are significantly lower ($p<0.05$) than that of the fittest robots evolved for environment A (figure 2, right). This indicates that as task difficulty increases a lower morphological complexity suffices to achieve high performance and supported by related work [12], [37] similarly demonstrating that simpler robot designs (lower morphological complexity) can achieve comparable or higher task task performance compared to more complex designs

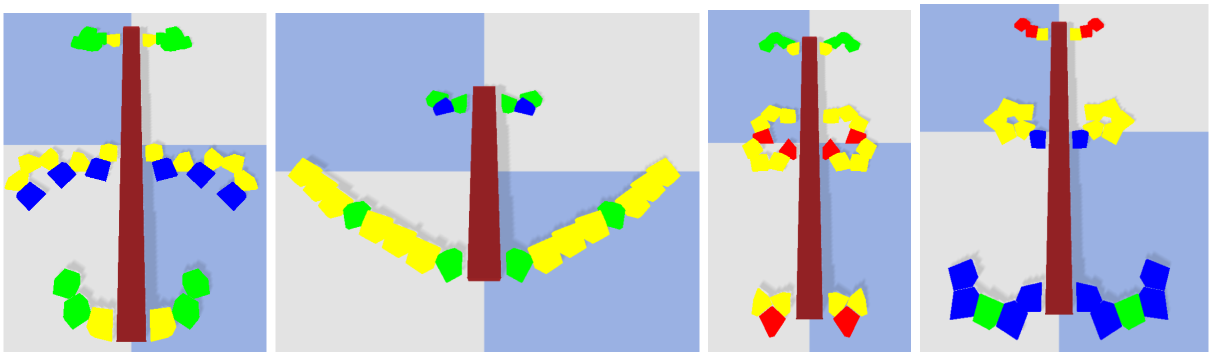

Fig. 3. Morphologies of highest performance (fittest) robots evolved in each environment. **Left:** Hexapod morphology evolved for the high friction, flat surface (environment A, table II). **Center-Left:** Quadruped evolved for the low friction, flat surface (environment B, table II). **Center-Right:** Hexapod evolved for the high friction, inclined surface (environment C, table II). **Right:** Hexapod evolved for the low friction, inclined surface (environment D, table II).

(higher morphological complexity). Observing the morphological complexity of the fittest robot evolved (figure 2, right) per environment (table II), we note that, with the exception of environment B (Low-friction flat) the morphological complexity of evolved robots is higher than that of the pre-designed robot (*Manual robot* in figure 1) (achieving a significantly lower average task performance ($p<0.05$) per environments, figure 2, left). These results support the need for automated evolutionary robot design [2], via indicating evolved robots achieve a high task performance and suitable degree of morphological complexity for given environments. That is, required degree of morphological complexity is heavily influenced by the environment, but cannot be too simple or complex if optimal or near-optimal behavior is to be achieved (figure 2, right).

B. Evolved Morphologies and Materials

Further supporting the impact of suitable materials for morphological design, we observe the task-performance benefits of all evolved morphologies (figure 2, left), across all environments. That is, for each environment, robots with evolved material designs significantly out-perform ($p<0.05$), the best performing pre-designed robots, including the best performing that comprise one of 16 pre-set material types (section III). In terms of evolved material designs, figure 3 presents the morphology of the fittest robot evolved in each environment, where components are coloured either green, red, blue or yellow to denote different material types (combinations of varying friction and restitution values, section II-A). For clarity of visualization, note that specific component colours denote specific friction values, whereas restitution values can vary per component colour.

The fittest evolved robots (figure 3) also indicate, in addition to morphological complexity (figure 2, right), the importance of the material types in robot composition for adapting to varying environments. For example, observing the morphology of the fittest robot evolved for the most difficult task (figure 3, right), we note this robot uses all material types, (green, red, blue and yellow blocks defined by varying friction coefficients: 0.25, 0.5, 0.75, 1.0, respectively). Whereas, the other fittest robots, evolved in less difficult environments (figure 3, left, center-left, center-right), use only three of the material types. Also, the material composition of the morphology of the fittest robot evolved in environment D (table II) intuitively suits the environment type.

For example, each front leg is comprised of mostly high-friction (four blue blocks per leg) material that enables the robot to gain traction on an inclined slippery surface, and propel its body forward by force of leg movement. The middle-legs have a similarly beneficial material composition, that is mostly very high-friction (four yellow blocks per leg) material that (coupled with the paddle-like leg shape) enables the robot to stay fixed on an inclined slippery surface while the front legs elevate to move forward. The robot's back legs also serve the function of helping the robot maintain stability while the robot's other legs are moving. The back-legs mostly used lower friction (two red blocks per leg), where a lower friction was suitable given that the main function of these back-legs was to maintain overall stability as either the middle or forward legs moved. These results are supported by related work on adaptive robot morphology similarly demonstrating benefits of evolving material compositions in robot design [31] and evolving such compositions [38], [39] as a means to optimise robot behavior across varying tasks.

Figure 3 (left) presents the hexapod morphology of the fittest robot evolved for high friction, flat surface (environment A, table II). Each front-leg comprises three blocks and two material types (one yellow and two green blocks). Each middle-leg comprises eight blocks and two material types (five yellow and three blue blocks). Middle leg-ends (arc-shapes formed by three yellow, two blue blocks) provide these middle-legs extra flexibility and control. Observing this robot's gait in environment A, this enables the robot to use this added flexibility to gain more traction on a high friction surface and fling itself forward for added mobility. The two back-legs each comprise 10 blocks, also of two material types (eight green, two yellow blocks). These back-legs have four (green) blocks clumped together into flat flipper-like structures. Gait observations reveal that these appendages are similarly used to gain traction and in concert with a jumping motion that propels the robot forward. Videos of the gaits of the fittest robots, evolved in each environment, are available online [33].

Figure 3 (center-left) presents the quadruped morphology of the fittest robot evolved for low friction, flat surface (environment B, table II). Each front-leg comprises eight blocks of two material types (six yellow, two green blocks). This robot's front legs are longer and more rigidly connected compared to the fittest robots evolved in other environments. This enabled these appendages to make connect (at legs length) with the ground ahead of the robot and use traction gained to pull itself forward until the legs returned to the position shown in figure 3. Gait observations also show the back-legs keep the robot fixed in position while the front-legs move forward to make contact with the surface ahead of the robot. As such these back-legs are relatively short, comprising three blocks each, but with a different material combination (two green, one blue block). These back-legs thus enable the robot to maintain traction on a low traction surface, while the front-legs are not in contact with the surface.

Figure 3 (center-right) presents the hexapod morphology of the fittest robot evolved for a high friction, inclined surface (environment C, table II). Each front-leg comprises three blocks of two material types (two yellow, one red block). Each middle-leg comprises eight blocks of the same two material types as front legs (six yellow blocks, two red blocks), and evolved to uncurl and curl back into the position shown in figure 3, as part of the robot's gait. Each back-leg comprises four blocks of two material types (one yellow, three green blocks). Overall, the robot's six legs enable it to maximize leg contact with the surface, where each leg's material composition enables traction, while the robot uses the uncurling-curling middle legs to propel its body up the incline.

Figure 3 (right) presents the hexapod morphology of the fittest robot evolved for a low friction, inclined surface (environment D, table II). Each front-leg comprises five blocks of two material types (four blue, one green block). Dissimilar to the fittest evolved robot evolved for the low traction incline (environment C), this robot evolved relatively long front-legs with a material combination better suited to gripping a low friction (slippery), inclined surface (table III). Also this robot used movement of its front legs to propel its body forward, where the middle and back legs are mainly used to maintain traction on the inclined, slippery surface, while the front-legs move. Each middle-leg comprises six blocks of two material types (five yellow, one blue). These middle-legs have evolved a paddle-like shape which, in contact with the surface, assists the robot in keeping traction on the inclined surface while other legs move. As with the fittest robots evolved for environments A-C, the back-legs are relatively short, each comprising three blocks of two material types (two red, one yellow).

C. *The Efficacy of Multi-Level Evolutionary Robot Design*

This study's results present the next step in evaluating the efficacy of MLE [5], a multi-level bottom-up evolutionary quality-diversity [24] robot design method. Evaluation refers to gauging ambulation behavior performance (in comparison to pre-designed robots), across increasingly difficult tasks. Task difficulty is defined as surface friction (low or high, tantamount to icy or rough terrain) and surface inclination (flat or sloping upwards). As with previous work [6], we focused on evolutionary design of legged robots where MLE generates robot morphologies suitable for given environments, via first selecting suitable materials to comprise modular components, then combining components into functional appendages and finally attaching configurations of appendages to a torso to achieve a fully functional (ambulating) robot morphology.

Overall, results indicate two key contributions. First, further demonstrating the efficacy of MLE for evolutionary robot (morphological) design, where morphologies are embedded with simple controllers actuating component joints (section II). MLE evolved robot morphologies generated suitable gaits as the robot interacted with its environment, significantly out-performing (distance covered) pre-engineered robot designs. This also provides support for the *morphological computation* hypothesis [40], via further demonstrating the benefits of adapting material composition to off-load computation for suitable behaviors (effective gaits in this case) from the robot's controller to its morphology (legged structure and material composition in this case). The benefits of evolving material compositions as part of robot design for changing environments has been similarly demonstrated in various soft-robotic ambulation [38] and object gripping [39] tasks. More broadly, our results contribute to the notion that the environment strongly influences one's morphology which in turn determines types of possible behaviors [13].

Second, these results contribute to a growing range of evolutionary robotics studies on emergent morphological complexity in robots that must adapt to various environments [15], [20], [21], [23] (in this study, environments were increasingly difficult to ambulate across). Specifically, we further elucidated the degree of morphological complexity necessary in order for robots to effectively ambulate across increasingly difficult environments. Supporting related work [12], [37], our results indicate that simpler morphologies achieve higher task performance compared to higher complexity morphologies, also supporting the notion that pre-designed morphologies suitable for any given task environment is impractical in most cases.

V. Conclusions

This study applied *Multi-Level Evolution* (MLE) robotic design via evolving materials comprising components and components comprising morphology. Results indicate MLE evolved robots effectively ambulate across increasingly difficult task environments, out-performing robots pre-designed for such environments. MLE evolved robots comprised component material types suitable for specific environments. Environment suitability of MLE evolved morphologies was supported by task-performance comparisons with pre-engineered robot designs using other materials. Results also indicate the highest performing MLE evolved robots were defined by a significantly lower morphological complexity (compared to pre-engineered and other MLE evolved designs), further supporting the notion that the desirable degree of design complexity is non-intuitive and difficult to ascertain *a priori*. Overall, our results further support the efficacy of MLE as an evolutionary robotic design method. Future work will incorporate a broader spectrum of materials, components and thus possible morphologies as well as evaluating the robustness of MLE robot designs across changing task environments using evolutionary controller-morphology transfer [41], [42].

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