Morpho-Material Evolution for Automated Robot Design

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ABSTRACT

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 hierarchical 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.

CCS CONCEPTS

• **Computing methodologies → Evolutionary robotics**.

KEYWORDS

Evolutionary Robotics, Multi-Level Evolution

ACM Reference Format:
Bilal Aslan and Geoff Nitschke. 2024. Morpho-Material Evolution for Automated Robot Design. In *Genetic and Evolutionary Computation Conference Companion (GECCO '24 Companion), July 14–18, 2024, Melbourne, Australia.* ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/3583133.3590528

1 INTRODUCTION

Currently, robot morphologies (sensory-motor hardware) and controllers (control software) must be re-engineered for every new application. This paper presents research extending and contributing to automated evolutionary robot design methods. The *Multi Level Evolution* (MLE) framework [2] 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 layer), then evolving the types of components to comprise the robot morphology (component layer), and finally evolves the composition and interaction of components (morphology layer).

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GECCO '24 Companion, July 15–19, 2024, Melbourne, Australia
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ACM ISBN 979-8-4007-0120-7/23/07.
https://doi.org/10.1145/3583133.3590528

Exploration versus exploitation in the MLE optimisation process is based on *Quality Diversity* (QD) [18], where solutions are discovered via exploring various feature dimensions. Here, 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-layer bottom-up approach enables the discovery of a vast range of robot designs by virtue of solutions optimised at each layer comprise re-usable solutions optimised at the layer 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 layers. A second benefit is that MLE is scalable to a higher number of features per layer since MLE evolutionary search concurrently and independently operates on each layer [2].

MLE uses QD to balance exploitation versus exploration of vast solution spaces (for example, robot body-brain design). QD methods [18] use specially designed evolutionary optimization using maps of high quality 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 optimisation 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 [3] and for other robotic adaptation tasks [11, 17], as well as robots designed for more complex tasks such as reconnaissance and gathering [12, 16]. Our main objective is to extend previous work on MLE legged robot design[2], providing further evidence supporting the efficacy of MLE for robotic design.

2 METHODS AND EXPERIMENTS

MLE uses CVT-MAP-Elites [19] for multi-layered hierarchical evolutionary design. The bottom layer is the materials layer (comprising materials with pre-generated properties), next is the components layer (combining point-based shape grammars to generate robot legs), and last is the robot layer (combines legs into complete functional morphologies). The MLE method is fully described in previous work [2], so here we present a summarized version only.

Material, Component & Robot Layer: At the material layer, material types are represented as combinations of *friction* and *restitution* coefficient values, constrained to the range: [0.25, 0.50, 0.75, 1.0], resulting in 16 material types. At the component layer, sets of connected components (robot legs) are represented as shape grammars [20], where individual component shapes (irregular polygons) are represented as point clouds [13] with an associated material type. At the robot layer, 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.

Material, Component & Robot Evolution: Map-Elites [19] 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 layer and three features at the robot layer (table 1), 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 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 1). Similarly, at the robot layer, 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 1). An evolved number of (pairs) of evolved legs are attached to the robot torso (applied symmetrically), to form a complete robot morphology. The component layer 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 layer fitness function was defined as the portion of an environment's length ([0.0, 1.0]) that an evolved robot traversed in a task trial (table 1).

Robot Controller Evolution: 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), N depended on the number of components (in each leg), and each controller was defined by a sinusoidal wave actuation [2]. All controller variables (*amplitude*, *frequency*, *phase*, and *offset*), normalized to: [-1.0, 1.0], were optimized using a (1+1) EA [7], where the number of variables depended on the number of components and non-fixed joints. Controller parameter evolution and the interaction of all component controllers thus determined a robot's overall (gait) behavior.

Pre-Designed Robots: To demonstrate benefits of MLE evolved robots across various task environments (section 2.1) 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. We use a pre-designed (hexapod) morphology from previous work [2], where the key difference is previous work only tested one property type (friction = 0.75, restitution = 0.75), whereas we evaluated 16 material types. Each leg comprised four square polygons, each with friction and restitution coefficients of 0.75. In the robot simulator [2], 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 2.1).

Parameter	Value
MAP-Elites	
Generations (Both layers)	1000
Component layer features	Mean component *friction* *restitution*, leg size leg complexity [2]
Robot layer 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

Table 1: Method & Experiment Parameters

Task	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

Table 2: Environments and associated task difficulty.

Task	Materials (Friction, Restitution)
A	Yellow (1.0, 0.75), Green (0.25, 0.25), Blue (0.75, 0.5)
B	Yellow, Green, Blue
C	Yellow, Green, Red (0.5, 0.25)
D	Yellow, Green, Blue, Red

Table 3: Evolved material types (friction, restitution) of fittest robot evolved (Figure 2) in each task environment (table 2)

2.1 Experiments

Experiments ran on custom robot simulator [1] using MLE [2] to evolve legged robot designs suitable for various environments (Table 2). Task environments (*A*-*D*, table 2) 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 2). However, 0.05 indicated relatively low traction, so coupled with an inclined surface this was the most difficult environment to traverse (*difficult*, Table 2). Robot task-performance was evaluated as the portion of environment length covered in one task trial (15 seconds, Table 1). 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.

Evaluation experiments tested the fittest MLE robot evolved for each environment versus a robot *pre-designed* for the same environment as follows. First, versus the pre-designed hexapod with a constant material type per component (friction=0.75, restitution=0.75) taken from previous work [2]. Second, versus the best performing of 16 pre-designed hexapod morphologies [2], where each pre-designed robot used one of 16 different material types. 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 [2], or the pre-designed robot (using one of the 16 material types, section 2) in a simulation task trial of 15 seconds (Table 1), replicating each of the four task environments (Table 2). 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 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), and average task-performance was computed over the 10 task trial repetitions for evolved versus pre-designed robots. Table 1 presents all MLE and experiment parameters. All other parameter values are as in related work [2].

3 RESULTS AND DISCUSSION

We first examine comparative average task performances of MLE robots evolved per environment and the highest task performance of 16 pre-designed robots (section 2) and the four best performing robots with various pre-defined materials, for the pre-designed robot morphology (section 2.1), in the same environments. Pair-wise statistical tests applied between the average task performance results of MLE evolved versus the pre-designed robot (section 2.1) indicate MLE evolved robots achieve a significantly higher average task performance (p<0.05) across all environments (Figure 1, left). Results data were non-parametric, found via a Kolmogorov–Smirnov normality test with *Lilliefors* correction [9]. Mann–Whitney U tests (p<0.05) were applied in pair-wise comparisons with Effect Size [4] treatment (all statistical test results are available online [1]).

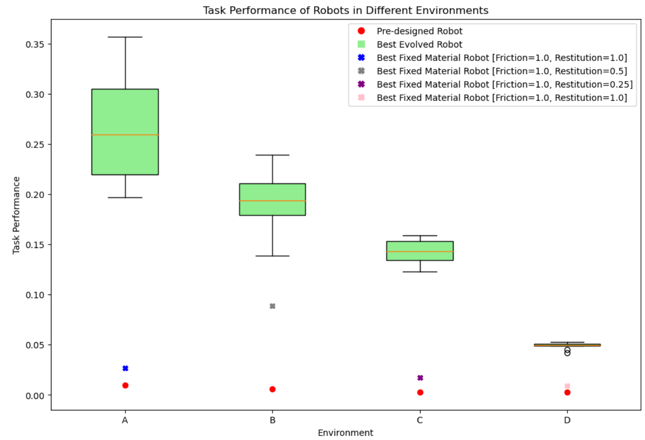

Figure 1: Average maximum task-performance of evolved (box-plots) versus pre-designed robots (red dot, colored stars).

Table 3 presents the evolved material composition (morphology) for the fittest (highest task-performance) robot evolved in each environment (Table 2). Supporting the impact of suitable materials for morphological design, we observe the task-performance benefits of all evolved morphologies (Figure 1), 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 preset material types (section 2.1). In terms of evolved material designs, Figure 2 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). 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 2) indicates the importance of the material types for adapting to varying environments. For example, observing the morphology of the fittest robot evolved for the most difficult task (Figure 2, 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 2, left, center-left, center-right), use only three of the material types. Also, the material composition of the fittest robot evolved in environment *D* (Table 2) 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

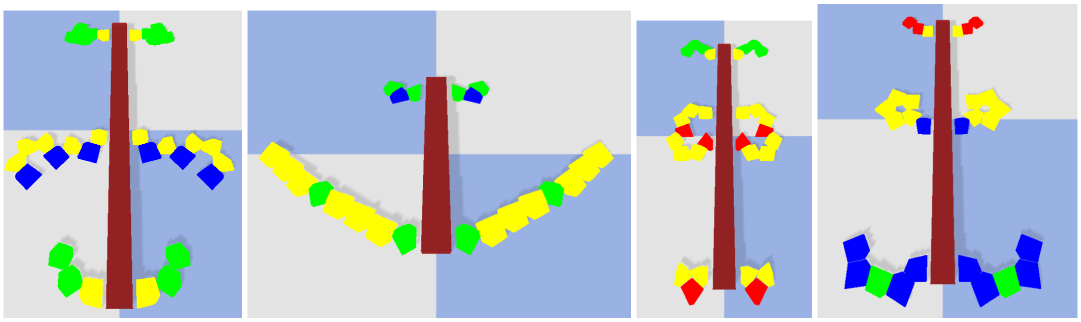

Figure 2: Morphologies of fittest robots evolved in each environment. *Left:* High friction, flat surface (A, Table 2). *Center-Left:* Low friction, flat (B, table 2). *Center-Right:* High friction, inclined surface (C, Table 2). *Right:* Low friction, inclined (D, Table 2).

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. Videos of the gaits of the fittest robots, evolved in each environment, are available online [1]. These results are supported by related work similarly demonstrating benefits of evolving material compositions in robot design [5] and evolving such compositions [10] as a means to optimise robot behavior across varying tasks.

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 2). 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 [14], 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 [10] and object gripping [8] tasks.

4 CONCLUSION

We applied 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 (defined by surface friction and inclination). Environment suitability of MLE evolved morphologies was supported by task-performance comparisons with pre-engineered robot designs using other materials. Overall, this study's results further support the efficacy of MLE as an evolutionary robotic design method. Future work will evaluate the robustness of MLE robot designs across changing task environments using evolutionary controller-morphology transfer [6, 15].

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