Co-Evolution of Robot Morphology and Control for Olympic Arena Navigation

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1 INTRODUCTION

This study investigates how the sequential co-evolution[1] of robot morphology (body) and neural network controllers (brain) contributes to efficient locomotion across a variety of complex terrains. The objective is to examine what body–brain combinations emerge when evolved for the Olympic Arena environment, which comprises three terrain types—smooth flat, rugged flat, and uphill sections—each terrain type introduces increasing levels of difficulty that requires suitable morphological adaptations and coordinated motor control.

1.1 Research Question

This study addresses the following research question:
How does the co-evolution of robot bodies and neural network controllers affect locomotion performance and adaptability across different terrains?

1.2 Background

Evolutionary robotics[6] employs evolutionary computation principles to automate the design of both robot body and brains. Rather than manually engineering body and brain structure, candidate solutions evolve through iterative selection, reproduction, and mutation based on their performance in a simulated environment. This process enables the emergence of adaptive, efficient locomotion behaviors over generations.

Co-evolution[1] draws inspiration from biological evolution, where the body and nervous system adapt together to environmental pressures. This interdependence allows robots to develop more natural and adaptive motion compared to approaches where body or brain is fixed. While many previous studies have focused on evolving either body or brain in isolation, such methods often limit adaptability and performance in unstructured environments[2].

In this work, Neural Developmental Encoding (NDE)[8] is utilized as an indirect encoding scheme for body generation. Evolved genotype vectors are transformed via a neural network into probability matrices that define the robot's structure, allowing for modular and scalable body evolution. Once the body is defined, each body undergoes independent brain evolution to optimize movement efficiency and adaptability.

By integrating these two evolutionary phases sequentially, this framework enables co-adaptation between body and brain, facilitating the emergence of robots capable of traversing diverse terrains with improved stability and performance. This work provides insight into how sequential body–brain evolution enables adaptive robotic behaviors in simulated environments.

2 METHODOLOGY

Our evolutionary robotics framework co-evolves robot bodies and brains (controllers) to achieve efficient locomotion across varied terrains. Neural Networks (NNs) were selected over Central Pattern Generators (CPGs) [5] due to superior performance and adaptability.

2.1 Algorithm Overview

Each generation consists of brain evolution followed by body evolution. Each body is evaluated using its best-performing brain, allowing focused optimization of brains while maintaining body diversity.

2.1.1 Body Initialization: Robot bodies are generated as genotypes that encode module type, connection, and rotation parameters. These vectors generate probability matrices that construct robot graphs (the body of the robot) with a maximum of 20 modules. A limit of 20 modules was set after observing that larger morphologies (e.g., 30 modules) produced overly bulky and inefficient robot designs.

To ensure that only functional morphologies are retained, a viability filter is applied. Each body undergoes random actuator movement tests over multiple 10-second trials, and only those moving more than 0.2 meters from their initial spawn position are included in the population.

2.1.2 Brain Evolution: Each body is paired with a population of brains represented as three-layer neural networks.

- **Input layer:** actuator positions (joint angles)
- **Hidden layers:** to introduce nonlinearities for learning complex locomotion behaviors
- **Output layer:** generates actuation signals for controlling movement

The neural network employs the tanh activation function for the input and hidden layers and a sine activation for the output layer. The output values are scaled by π to match the actuator control range and to prevent jittery movements. The sine activation was specifically chosen to try and naturally induce rhythmic and oscillatory patterns, thus promoting coordinated locomotion.
Evolution proceeds as follows:

- **Evaluation:** Each brain controls its corresponding body for a fixed duration. Additional time is awarded upon reaching predefined checkpoints, which promotes meaningful movement and filters out non-functional designs.
  - 0.2 m $\rightarrow$ +5 s (flat terrain)

- 0.5 m $\rightarrow$ +45 s (rugged terrain, early)
- 1.5 m $\rightarrow$ +20 s (rugged terrain, further)
- 2.5 m $\rightarrow$ +45 s (new surface/start of slope)
- 3.0 m $\rightarrow$ +60 s (steep slope)

- **Selection:** Tournament selection favors brains achieving higher fitness (distance traveled). The tournament size has high selection pressure, preventing the brains to converge quickly, thus losing diversity due to the low population number.
- **Variation:** A uniform crossover was implemented with a population-level rate of 1.0 and a gene-level crossover probability of 0.5. To introduce variation, Gaussian mutation was applied with a population-level rate of 0.5 for brain weights and a per-gene mutation probability of 0.6. These rates were selected to maintain an effective balance between exploration of the search space and exploitation of promising solutions.
- **Survivor Selection:** An elite brain [7] is retained in each generation, ensuring that the best-performing solution is preserved. The remaining population is combined with the offspring and updated using a steady-state selection approach, where tournament selection determines the survivors for the next generation. This method allows fit parent individuals to remain if their performance exceeds that of the offspring, maintaining evolutionary stability while promoting gradual improvement.
- **Termination:** Evolution continues until fitness improvement stagnates for a patience threshold of 7 generations, at which point brain evolution for that body is halted, indicating that the robot's brain is no longer making meaningful progress.

2.1.3 Body Evolution: After brain evolution, bodies are evaluated using their best brains. The fitness of a body is defined as the fitness of its best brain corresponding to it.

The body population undergoes the following:

- **Selection:** Tournament selection [7](size 4 to keep the selection pressure high) for selecting the parents.
- **Variation:** Crossover and mutation are analogous to brain evolution.
- **Offspring Evaluation:** Offspring are evaluated by training their corresponding brains to determine fitness.
- **Population Update:** The parent and offspring populations are combined, allowing parent bodies with higher fitness than their offspring to persist in the population.
- **Survivor Selection:** One elite individual is retained, and tournament selection is applied to select the remaining individuals for the next generation.

This process is repeated over multiple generations.

2.2 Fitness Function

Fitness is defined as the negative Euclidean distance to a fixed target [5, 0, 0.5], promoting forward locomotion.

$$f = -\sqrt{(x_{\text{target}} - x_{\text{final}})^2 + (y_{\text{target}} - y_{\text{final}})^2 + (z_{\text{target}} - z_{\text{final}})^2}$$

2.3 Experimental Setup and Parameters

Table 1 summarizes the configuration of the evolutionary algorithm.

Table 1: Evolutionary Algorithm Configuration

Parameter	Body	Brain
Representation	3×64 vectors	Weight matrices
Population Size	10	40 per body
No. of Generations	50	50
Recombination	Uniform crossover (Rate=1.0)	Uniform crossover (Rate=1.0)
Mutation	Gaussian (μ=0, σ=0.5)	Gaussian (μ=0, σ=0.5)
Mutation probability (Individual and Gene)	0.6	0.6
Parent selection	Tournament (k=4)	Tournament (k=10)
Survival selection	Tournament (k=4)	Tournament (k=10)
Termination	50 generations	50 gen./Patience=7

All experiments were conducted using a fixed random seed (seed = 50) to ensure the reproducibility of body and brain initialization, as well as stochastic operations such as mutation and selection.

2.4 Computational Budget

The total computational budget is 2,000,000 fitness evaluations (50 body generations × 10 bodies × 50 brain generations × 40 brains; times 2x for both parents and children). Given the substantial computational time required, we implement check-pointing: the best body from each generation is saved, allowing early stopping while preserving optimal solutions found up to that point.

3 RESULTS AND DISCUSSION

3.1 Evolutionary Trajectory

Evolution achieved a substantial performance improvement over six generations(Generations 0-5), after which evolution was halted due to time constraints. The average fitness progressed from −5.18 in generation 0 to −3.84 in generation 5, representing approximately 1.34 meters of improved forward travel — a 25.9% increase in fitness. The best fitness within each generation improved from −4.72 to −3.63, confirming that both population-wide adaptation and elite individual performance advanced consistently throughout the evolutionary run.

The evolutionary trajectory exhibits two distinct phases:

Phase 1 (Generations 0-2): A period of rapid improvement, with the average fitness curve showing a steep rise and the best fitness reaching a strong early peak. This indicates that the initial generations effectively exploited readily available improvements in both morphology and control. The wide standard deviation bands suggest high population diversity, with numerous viable but distinct locomotion strategies emerging in parallel.

Phase 2 (Generations 2-5): A period of gradual stabilization, where fitness improvements slowed as the population converged toward effective morphologies. The narrowing standard deviation bands indicate reduced variance and increasing consistency across individuals. Despite this, the best fitness continued to rise slightly, showing that top-performing morphologies were still being refined while overall diversity was maintained enough to prevent premature convergence.

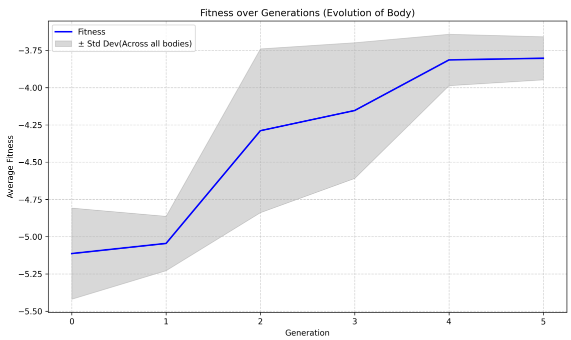

Figure 1: Average fitness of the population across generations. Average fitness steadily improves from generations 0 to 5, while decreasing variance indicates convergence toward effective morphologies and controllers

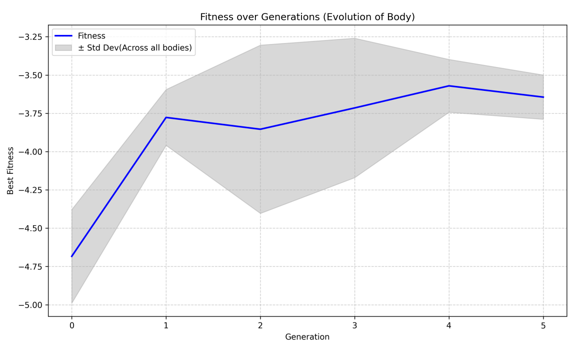

Figure 2: Best fitness achieved in each generation. Best fitness rises rapidly at first and then gradually improves, indicating optimization of elite morphologies.

3.2 Best Individual Morphology and Control

The final best individual comprises a 20-module body structure with 8 hinge actuators. The joint position vector is 8-dimensional (8 hinge angles); if joint velocities are included, the full joint state is 16-dimensional (8 positions + 8 velocities). Morphological analysis reveals bilateral symmetry with alternating brick-hinge patterns creating articulated appendages. The controller network contains 1,696 parameters: $\mathbf{W}_1 \in \mathbb{R}^{14\times32}$ (448 params), $\mathbf{W}_2 \in \mathbb{R}^{32\times32}$ (1,024 params), $\mathbf{W}_3 \in \mathbb{R}^{32\times7}$ (224 params).

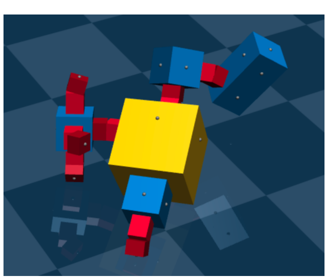

Figure 3: Visualization of the best robot's body structure showing modular composition.

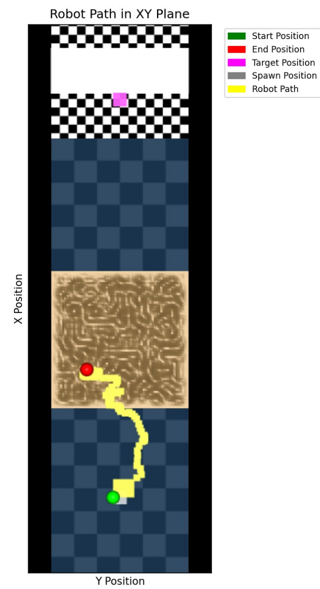

Figure 4: Best robot's path (Yellow line) from spawn point (green) to final position (red) overlaid on Olympic Arena environment in 100 seconds

The robot's locomotion relies on rapid oscillations and occasional jumps rather than smooth gaits, achieving forward progress with minor instability and lateral drift. Rudolph [3] demonstrates that an evolutionary algorithm with mutation and elitism can theoretically reach the global optimum given sufficient time, suggesting that extended evolution could produce more stable and efficient locomotion.

3.3 Algorithm Performance Analysis

Co-Evolution Dynamics: The hierarchical co-evolution framework effectively paired morphologies with specialized controllers [1, 2], as shown by diverse fitness responses(large standard deviation band in Fig. 1). Evolution progressed through two clear phases: a rapid improvement during the initial generations followed by gradual stabilization as the population converged. The evolved robot consistently traversed flat terrain and reached halfway through the rugged plain.

Computational Efficiency and Resource Allocation:

Approximately 240,000 evaluations (~2,000 per body) were performed for 6 generations(gen 0-5). Adaptive evaluation prioritized high-performing individuals.

Adaptive Evaluation Effectiveness: The checkpoint system efficiently allocated resources, with high-fitness individuals (x > 0.5m) triggering multiple reruns for a thorough evaluation, while poor performers received minimal simulation time. For example, individuals crossing checkpoint 2.5m received an average evaluation of 135 seconds versus 15 seconds for those failing checkpoint 0.0m.

Morphological Constraints and Opportunities: The NDE's [4, 8] discrete module types and connection rules constrain the search space, resulting in some configurations that are more challenging to control. The viability filter successfully eliminates non-functional designs, while marginally viable morphologies contribute to genetic diversity, supporting the evolutionary process. These constraints highlight areas for potential refinement, such as exploring continuous module parameters or adaptive architectures to enhance efficiency and control.

3.4 Critical Reflection and Unexpected Findings

Characteristics of the fitness landscape: The steady yet oscillating fitness trend during Phase 2 reflects a rugged fitness landscape with multiple local optima. The persistent standard deviation across generations suggests that these optima represent distinct morphological–control strategies, not mere variations of a single design. This diversity indicates the system's strong exploratory capability and its ability to maintain multiple viable locomotion patterns across different terrain types.

Early Stopping Impact: Evolution was halted after six generations due to time constraints, though fitness continued to rise gradually toward the end of the run. The consistent improvement and narrowing variance indicate effective convergence without premature stagnation. Extending the number of generations or selectively increasing the evaluation budget for high-performing morphologies could further refine controller stability and overall performance.

Limitations: The current distance-only fitness function focuses on forward displacement, providing a clear and measurable optimization target. While it does not explicitly account for energy efficiency or gait smoothness, these factors present opportunities for future exploration. Similarly, the relatively small population size and fixed 32-neuron hidden layer were sufficient to evolve functional solutions, though adaptive network sizing and larger populations could further improve diversity and control. The discrete module types of the NDE, while constraining, ensured the generation of viable morphologies and highlight directions for future work using continuous parameters or more flexible architectures.

Computational Considerations: The limited number of generations and evaluation budgets constrained the total search depth. Despite this, the framework successfully evolved robots capable of traversing flat terrain and reaching halfway through the rugged plain, confirming the method's effectiveness even under restricted computational resources. These findings demonstrate the scalability and adaptability of the hierarchical co-evolution framework, reinforcing its potential for more complex environments and extended evolutionary runs.

4 CONCLUSION

This research implemented and evaluated hierarchical co-evolution for robot morphology and neural control optimization. Over six generations, the framework successfully evolved a functional robot capable of crossing flat terrain and reaching halfway through the rugged plain in the Olympic Arena environment. These results demonstrate the feasibility of co-evolving body–brain systems to achieve adaptive and resilient locomotion under constrained computational budgets.

Key Findings:

(1) The hierarchical co-evolution framework effectively paired morphologies with specialized controllers, achieving a 25.9% improvement in fitness and demonstrating coordinated adaptation between body and control.
(2) The evolved robot exhibited consistent forward displacement using oscillatory yet stable movements, indicating successful controller learning within the limited evolution window.
(3) Fitness progression showed variability across morphologies, indicating the presence of multiple viable locomotion strategies and the significant influence of body structure on achievable performance.
(4) Different body designs reached peak performance at different stages of brain evolution, validating the effectiveness of per-body controller optimization.

Limitations:

(1) Small population size (10) and early termination (After 6 generations) limited exploration of long-term evolutionary dynamics, suggesting the potential for enhanced performance with extended runs.
(2) The distance-only fitness metric prioritizes forward displacement but leaves room for integrating energy efficiency, stability, and gait smoothness.
(3) Fixed neural architectures and discrete module representations constrained adaptability; adaptive network sizing and continuous morphological parameters could expand the solution space.
(4) Computational cost (~40 hours) limited the number of iterations, highlighting opportunities for parallel evaluation or progressive complexification strategies.

Future Work:

- Introduce multi-objective fitness functions [7] incorporating energy efficiency, stability, and smoothness to evolve more robust locomotion strategies.
- Implement adaptive hidden layer sizing and extended brain evolution budgets (30–40 generations) for complex morphologies.
- Explore progressive complexification [4], starting with simple morphologies and incrementally adding modules, to scaffold evolution toward more capable designs.
- Apply curriculum learning across increasingly challenging terrains to foster generalist locomotion strategies.
- Investigate parallel co-evolution with periodic cross-evaluation to reduce computational cost while maintaining effective morphology–controller coupling.

Overall, this study demonstrates the potential of hierarchical co-evolution to generate functional and diverse robot locomotion strategies, providing a strong foundation for further refinement and more sophisticated evolutionary experiments.

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