Co-optimization of modular robots for locomotion and energy-efficiency

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Abstract. Evolutionary robotics is concerned with designing the morphology and controller of an autonomous robot to operate efficiently in its environment. Previous research has shown that including energy consumption as a fitness parameter for the evolution of modular robots, results in better behavioural traits. In this paper, we investigate how these behavioural traits vary with more body parts, namely the joints. Increasing the number of joints of a modular robot increases the energy efficiency of the robots as the morphology also adapts accordingly. The results show that by including energy consumption, the evolution process gives us efficient morphologies to cover maximum distance and use less energy.

Keywords: Evolutionary Robotics, Energy-efficiency, Locomotion, Multi-Objective Optimization, Modular robots

1 Introduction

A general theory of biological evolution suggests that life evolves as a property of the utilization of energy [1], [2]. For biological species, where animals have to locomote from place to place in search of food or to avoid being food, efficiency is the key; how can one go the greatest distance using the least amount of energy? [3] [4]. In every environment imaginable, these species have experienced unique pressures, mechanical demands and functionality challenges. These gave rise to highly specialized organisms that are incredibly efficient in using available resources [5], [6]. Over the course of successive generations of populations of organisms, adaptation [7] through natural selection has been the key to the evolutionary process.

Evolutionary Robotics(ER), based on biological mechanisms, is a multidisciplinary approach to robot design. It applies evolutionary computation techniques [8] to design and evolve robots that are best suited to fulfill their tasks in their specific environments. This includes the evolution of both the robot controller (i.e. the 'brain') and the morphology (i.e. the 'body') of the robot, over generations under certain selective pressures [9]. Analogous to the natural evolution, the system performance of an autonomous robot, which operates on a battery, depends highly on itś energy consumption [10]. The limiting factor of the battery life increases the reality gap [11]of the ER systems. Most systems use specified thresholds and scheduled charging times to optimize energy usage [12]. Green scheduling algorithms have also been utilized for the optimization of energy consumption in various applications [13]. These methods are limited in terms of fixed robot morphology. A crucial way to tackle the energy demands is to evolve the robots morphologically so that they can adapt their behaviour more energy-efficiently to fulfill their task [10]. Similar research has observed that inclusion of the energy consumption as a parameter for the evolution of robots shows better behavioural traits [10].

A real-world mechanical robot would have a lot of components that lead to it′s energy consumption like motors, sensors and microcontrollers [14]. Besides the useful energy used to fulfilll the task, there is considerable energy leakage as well. Prior works [10] have evolved robots that move efficiently while increasing the number of joints. A considerable question here would be that increasing the number of joints also increases the energy consumed by those joints. The motivation of this paper is to investigate how the energy efficiency and locomotion of a robot are affected by the increase in the number of joints. We only consider the energy used by the servos of the joints and do not take into consideration the energy used by the microcontroller and other components.

In the current paper, newborn robots are provided with the energy of a battery and simulated over a given period of time. They are evaluated by the distance they moved in that time period. The energy left at the end of the simulation time is also evaluated as a measure of the most efficient gait and the most advantageous morphology. Our desired Pareto optimal solution is the region of the objective space with high remaining energy and maximum distance moved. Hence, we take a multi-objective optimization approach using NSGA-II [15] to get the most optimal solutions [16]. The optimization problem is defined as $\max_{x \in X} \{f_1(x), f_2(x)\}$, where X is the feasible set of solutions in the objective space and $f\{x\}$ represents the remaining battery energy and $f\{y\}$ represents the distance moved.

The structure of this paper is in the following manner: In Section 2, we explore the related work in this field. The System descriptions and the experimental setup has been explained in Section 3 and Section 4. The results and the corresponding analysis and discussions are done in Sections 5 and 6. In Section 7, we conclude this paper with a discussion on further research potentials.

2 Related Work

In robotics, effective locomotion strategies are a widely studied area. It is highly affected by the different environments, the tasks to be achieved by locomotion and different body shapes and sizes. A constrained robotic body proves limitations to the exploration of different domains of locomotion. The bio-inspired domain of robotics makes locomotion a learning process over the course of generations [17]. Optimizing adaptive locomotion [18],[19] in the face of uncertain dynamic conditions has been studied widely in the form of adaptable and reconfigurable modular robotic systems[20]. Multi-objective optimization of quadruped locomotion tackling body vibrations and gait performances have been studied in [21], [22], [17]. Lipson and Pollack have studied the combined evolution of robot morphology and controller using computational and experimental approaches [23]. Multiobjective optimization of modular robots inspired by snake bodies has been studied in [24]. Some studies inspired by snake bodies have examined the co-evolution of energy-efficient locomotion behaviours and morphological traits [24], [25]. Including energy consumption in the fitness of the evolutionary process has been shown to affect the average size of the robot bodies and their speeds [26]. Similar works done using the Revolve framework have found the CPPN encoding to bias robots with fewer joints as a means of energy conservation, in turn giving characteristic morphologies that indicated snake-like bodies with multiple limbs or more blocks [26], [10]. Building further on these findings, in our work, we test how the CPPNWIN encoding chooses the robot's morphology to energy-efficiently locomote if it were given more modules to build on, taking into consideration only the energy consumed by the joints.

3 System Description

For our experiments, we use the Revolve [27] toolkit along with Mujoco as the physics simulator [28]. Revolve implements and uses the evolutionary framework to run various evolutionary processes under different selective pressures and environments. Mujoco as a full-featured simulator is a very useful tool for model-based robotic systems. It provides a lot of access to multi-joint dynamics and sensor data and is used to evaluate the fitness of every new genotype.

3.1 Robot morphology

The robot's bodies are made up of cuboidal modules [29]. The morphology of the robots is decided by evolution. The are five different modules: core components, bricks, vertical joints, horizontal joints and touch sensors [29] [10]. The core module is the core of the robot's body which holds the microcontroller and battery, the bricks make up the body of the robot and the joints are attached to the robot's body using a servo motor. Additionally, we add torque sensors in the robot's joints while modelling the robots in the Mujoco environment. The hinge torque values from the joint servos are used for the calculation of the energy consumed by the robot.

Morphological evolution gives rise to unique behavioural traits like body balance and gait for locomotion. It helps the robots learn [30] to fulfill their task i.e. locomotion using the most efficient body phenotype and behaviours.

3.2 Robot controller

The robot's controller (i.e. the 'brain'), is implemented by a self-organizing artificial neural network called the Central Pattern Generator (CPG). It is used to mimic the biological rhythmic movement patterns in the absence of a phasic sensory input [31][32]. Since, the robot's morphology changes over the course of evolution, to obtain the optimal fitness value, the corresponding controller also keeps adapting to the morphology to help the robot execute it's task in the environment. This gives rise to various gait patterns[33] and behaviours.

3.3 Robot Encoding

The mapping of the genotype to the phenotype is implemented using the Compositional Pattern Producing Networks (CPPN-NEAT) algorithm[34]. This developmental encoding algorithm is capable of evolving and discovering symmetry and patterns with small variations in the genotypes, making it highly efficient in forming different morphologies of the robot. More details about the encoding system used in this framework can be found here [29].

3.4 Fitness

3.5 Energy efficiency

We add a battery module in Revolve that tracks the energy usage of every robot during its lifetime. We only consider the energy used by the servos of the joints and disregard the other forms of energy consumption. To replicate a real battery, we use a series of 2 900 mAh, 3.7 V Li-Ion batteries with an energy capacity of 3.33 Wh, rescaled to the simulation time. We denote this value by E_{Total}. The cumulative energy used by the robots at every *mjstep* of the Mujoco simulation time is calculated as :

$$E_{used} = \sum_{i=1}^{n} \tau\omega * t \tag{1}$$

where,

E_{used} = The total energy consumed by all the robot joints.
n = The number of joints in the robot's body
τ = The hinge torques
ω = The hinge angular velocity
t = *mjstep* of the Mujoco simulation time

We assume a constant energy consumption of 0.3 Wh by the other components of the robot. Also, to avoid inaccuracies of high precision values of the simulator and Revolve, we clamp the torque values of every hinge joint to 0.01, which means that robots with hinge torques below 0.01 Nm, will have torque values of 0.01 Nm. So, we define the energy supplied to the robot, E as :

$$E = E_{Total} - 0.3 \tag{2}$$

We check the E_{used} by the robot in comparison to E.

3.6 Locomotion

Locomotion is defined as the act of moving from one place to another. Animals move from one place to another by exerting forces on their external environment[35]. The distance the robot moves during its lifetime is calculated as the Euclidean distance between the beginning and end positions. If (x_0, y_0) is taken as the beginning position and (x_1, y_1) is taken as the end position, then the Euclidean distance is calculated as :

$$D = \sqrt{(x_1 - x_0) + (y_1 - y_0)} \tag{3}$$

where,

D = The Euclidean distance moved by the robot.
x,y = The robot coordinates in the coordinate system.

3.7 Energy Efficieny

For our experiments here, we have defined energy efficiency (η) as the distance moved by the robots per unit of energy used, as shown by the equation :

$$\eta = \frac{D}{E_{used}} \tag{4}$$

3.8 Stopping mechanism

The evolution process stops under two conditions :

- When the simulation time completes
- When the battery power drains out, irrespective of the simulation time. In reality, it does not make sense to have a robot with a negative energy level. To avoid that, we check for the remaining energy at every *mjstep*. This ensures that the robots have the updated energy level at every timestep. If for the next state, the energy required by the robot to locomote goes to a negative value, the previous state of the robot is taken as the final state.

4 Experimental Setup

The Revolve framework doesn't specify the number of joints to be used by the robots during their formation, rather it provides more freedom to the neural network to choose the maximum number of joints required for the efficient formation of the robot's body. Following the framework, to investigate the effect of the number of joints on the energy efficiency of the robots, we set up four sets of experiments, with varying numbers of maximum modules that the CPPNWIN is allowed to use, namely 10, 15, 20 and 25.

Initial simulations of the experiments resulted mostly in snakes with jumping behaviour. To mitigate this effect of force on the gait of the robots, we ran simulations with different values of position feedback gain (kp) and velocity feedback gain (kv), and accordingly tuned up the values of the PID controller. Even though Mujoco is a physics simulator, a realistic mapping of all the real-world forces and achieving the constraint dynamics is difficult [36]. MuJoCo is known to generate longer contact events with lower peak forces. This is due to the way in which it models the interaction between friction and contact dynamics [36]. This modelling approach leads to a slower dissipation of energy compared to other simulators, resulting in smoother and more realistic simulations of contact dynamics [37]. To determine the optimal value required for our models, a range of simulations were conducted using different values of *forcerange* ranging from 0.75 to 4 in increments of 0.5. We observed that the higher the *forcerange* value, the more the jumping behaviour of the snakes. In order to maintain an optimal level of realism in our robot's gait, we adjusted the *forcerange* parameter to a value of 1.0. We also clamp the hinge torque values to 0.01 to avoid inaccuracies in the models.

The multi-objective optimization problem is defined as the maximum distance moved by the robot using minimum energy. Similar results as in [10] was found, stating that larger robots covered up more space because of their size as compared to smaller robots. Nevertheless, the evolutionary process found a way of saving full energy power by forming clusters of blocks and tripping over. To avoid this erratic behaviour, we add selective pressures in the evolutionary process in the form of *distance threshold* and *remaining power threshold*. We set both thresholds at just the minimum value to push the evolution from those extreme values of no mobility and full energy.

We ran our four sets of experiments for 5 runs and collected the data for further statistical analysis. The parameters used for the experiments are shown in Table 1

Parameter	Values
Population size	100
Offspring size	100
Generation	50
Crossover Probability	0.8
Mutation Probability	0.8
Simulation time	20
Tournament size	4
Battery power	129
Number of Runs	5

Table 1: Parameters used for the evolutionary process of the robots

We provide a pseudocode of the evolutionary process in Algorithm 1 and a pseudocode of the ranking system using NSGA2 in Algorithm 2.

Algorithm 1 Pseudocode for the evolution process of the robots

procedure EVOLVE_ROBOTS()

$population \leftarrow random\_genotypes$

$ranking \leftarrow NSGA2(population)$

$generation \leftarrow 0$

for `generation<nr_generations` **do**

$parent\_tuples \leftarrow select\_parents(population, ranking)$

$offsprings \leftarrow crossover(parent\_tuples)$

$offsprings\_mutated \leftarrow mutate(offsprings)$

$population_combined \leftarrow population + offspring$

$ranking_combined \leftarrow NSGA2(population_combined)$

$population \leftarrow select\_survivors(population\_combined, ranking\_combined)$

$ranking \leftarrow NSGA2(population)$

$generation \leftarrow generation + 1$

end for

end procedure

5 Experimental Results

Algorithm 2 Pseudocode for ranking the robots, using NSGA2

procedure NSGA2(population)
    $fronts \leftarrow []$
    $population\_is\_empty \leftarrow False$
    while $population\_is\_empty = False$ **do**
        new_front = find_non_dominated_points(population)
        $fronts \leftarrow fronts + new\_front$
        remove the individuals inside new_front from the population
        if population is empty **then**
            $population\_is\_empty \leftarrow True$
        end if
    end while
    for `front in fronts` **do**
        sort individuals within the front by crowding distance
    end for
    $ranking \leftarrow []$
    for `front in fronts` **do**
        add individuals from the front in order to ranking
    end for
    return ranking
end procedure

In this section, we analyse the experiments described in the above sections. The code and the data for the experiment can be found here. To summarize the effect of the varying number of joints on the objective functions and energy efficiency, we plot a few graphs comparing across joints. Each figure in 1, 2,3, 4, presents the median value across 5 runs of the 100 robots in each generation, plotted across 50 generations. The first and the third quantiles are also included to visualize the variability of the robots. We also plot the median value of the energy efficiency across the 50 generations. A graph of the median value of joints across generations also shows how the evolutionary process adapted over the course of time. When provided with different maximum modules available for the network to use, we see a lot of spread of the number of joints of the robots across generations, while concentrating on a few joints more than the others. The graphs are shown in 1, 2,3, 4. To see the progress of the distance covered by the robots, across generations, we plot the maximum median distance per generation, along with the first and the third quartile, as shown in the above-mentioned graphs. The median values of energy efficiency also show an increasing pattern over the generations. For each of the datasets, we do the Kruskal-Wallis test to check for the median value across runs. We find all of the datasets to be quite significant ($p < 0.05$). It states that there is not much significant difference between the runs. The corresponding p-values are mentioned in the respective graphs.

6 Analysis and Discussion

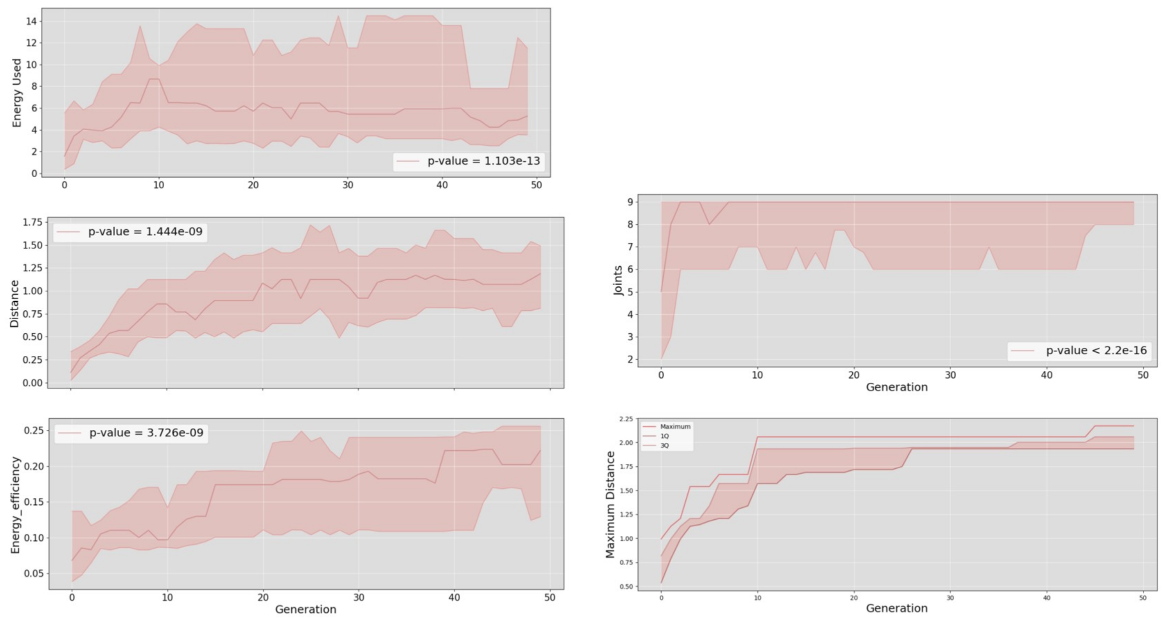


Fig. 1: Distribution of robots along with their behavioural traits over the generations, for maximum modules 10

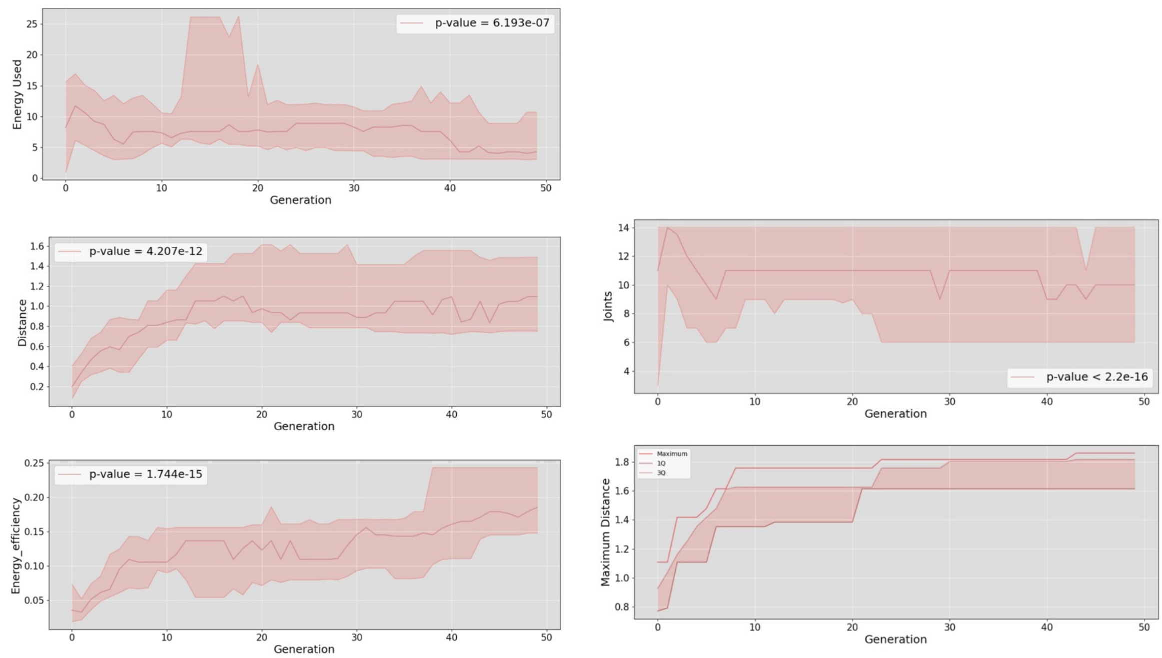


Fig. 2: Distribution of robots along with their behavioural traits over the generations, for maximum modules 15

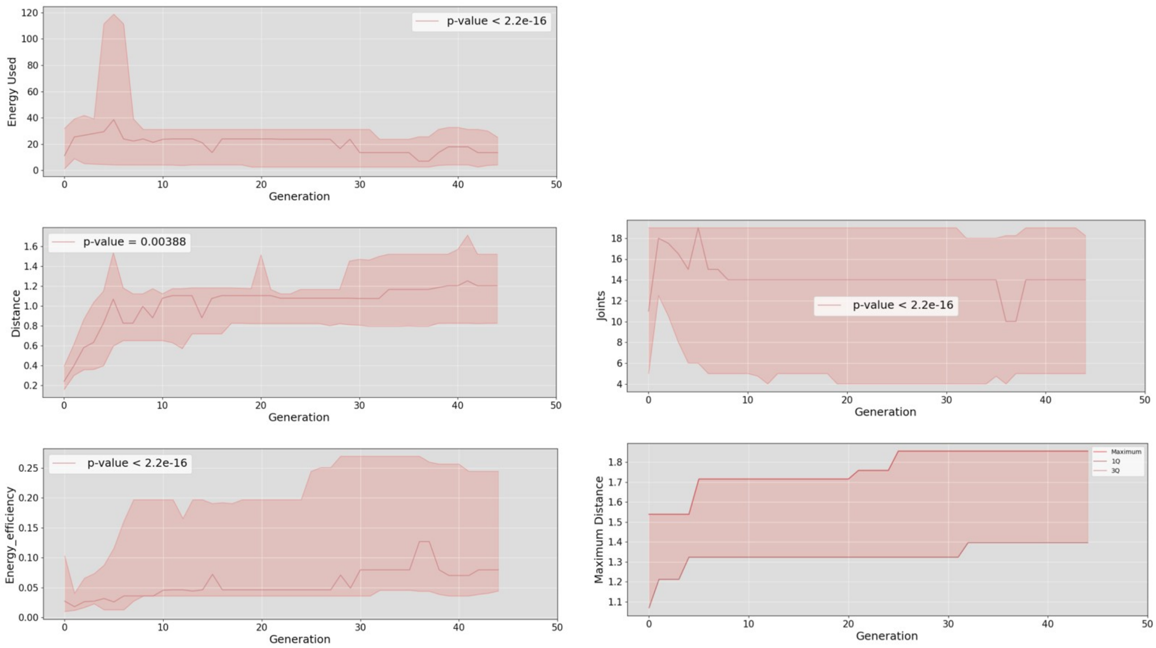


Fig. 3: Distribution of robots along with their behavioural traits over the generations, for maximum modules 20

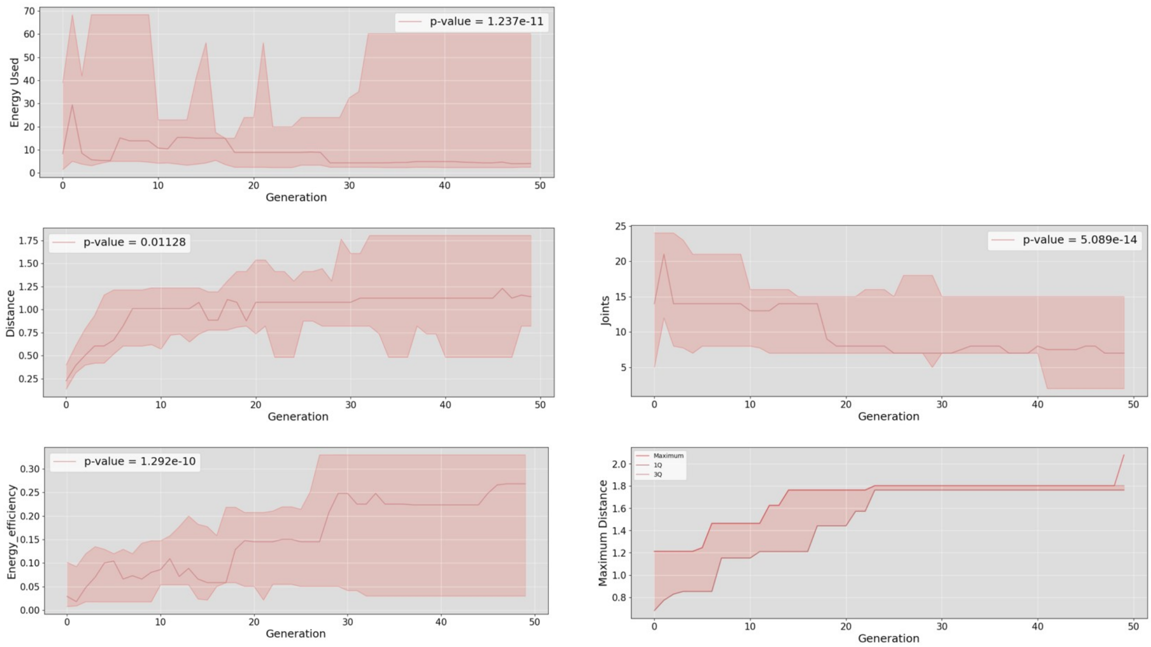
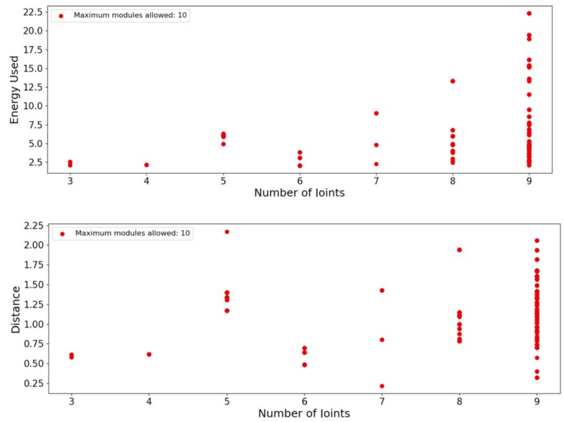
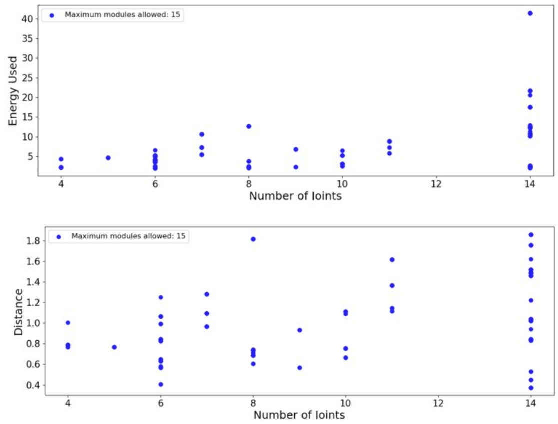


Fig. 4: Distribution of robots along with their behavioural traits over the generations, for maximum modules 25

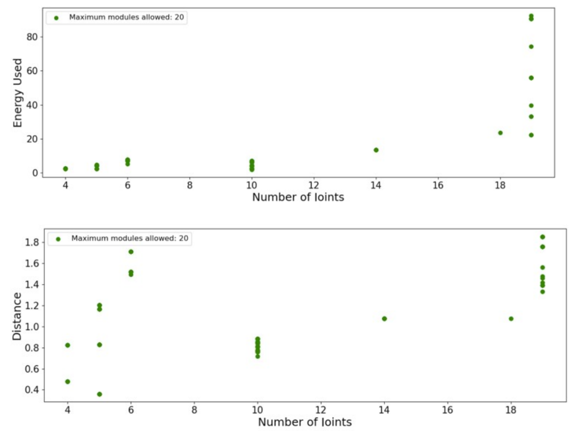


(a) Distribution of robots shown per joint number along with the Distance moved and Energy used, for maximum parts 10

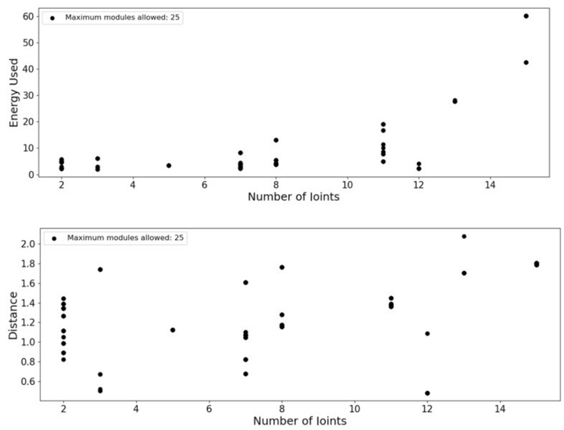


(b) Distribution of robots shown per joint number along with the Distance moved and Energy used, for maximum parts 15

Fig. 5: Distribution of individual robots per joint number for the last generation for all five repetitions for maximum modules 10 and 15



(a) Distribution of robots shown per joint number along with the Distance moved and Energy used, for maximum parts 20



(b) Distribution of robots shown per joint number along with the Distance moved and Energy used, for maximum parts 25

Fig. 6: Distribution of individual robots per joint number for the last generation for all five repetitions for maximum modules 20 and 25

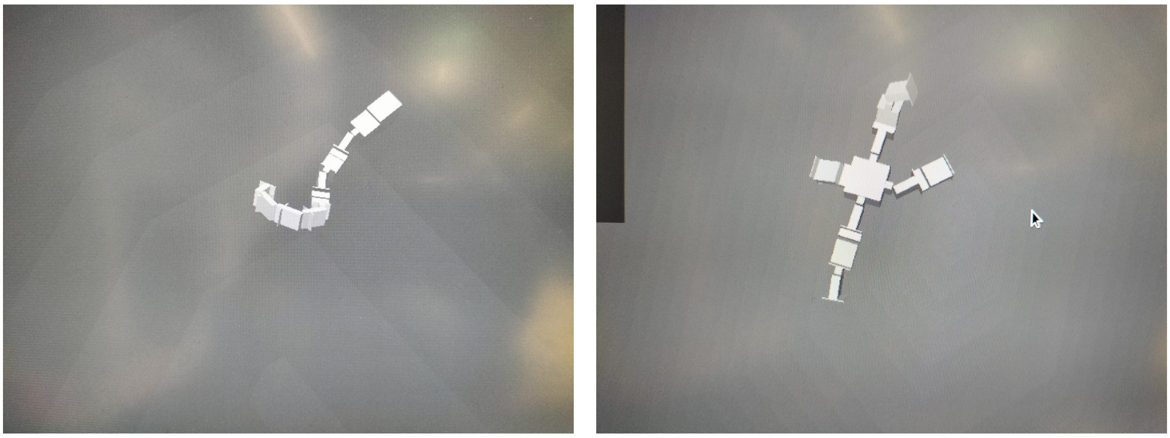


Fig. 7: Figures showing different morphologies of the robots in simulation, Part 1

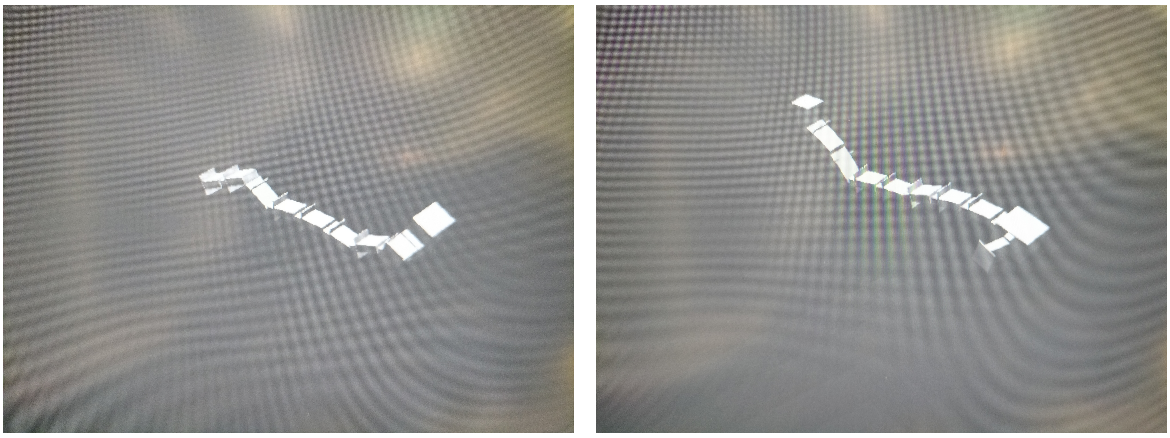


Fig. 8: Figures showing different morphologies of the robots in simulation, Part2

As evident from the graphs, we observe that across generations, the evolutionary process kept optimizing to find the most optimal morphology and gait to use the minimum energy and move the maximum distance. Thereby, increasing energy efficiency across the generations. We also notice a significant convergence of the joints over generations. From 1, 2, 3, we see that the number of joints has remained constant over several generations. In 5, 6, a significant concentration of individual robots is observed across specific joint numbers. We also see that the energy used and the distance moved increased with an increase in the joint number.

The most prominent morphologies that showed up in the Pareto fronts were the 4-legged robots and snakes, as shown 7 and 8. There were various sizes of the 4-legged and snake robots based on the number of modules the network was allowed to use. The 4-legged robot showed crawling behaviour, efficiently locomoting using the two extended limbs, whereas the snakes showed a sidewinding movement. The intuition behind choosing a gait that seemed more stable was to decrease the reality gap between a simulated robot and a real one. The gait of the 4-legged robot looked quite stable. In the case of the snakes, the sidewinding motion was stable for snakes with less number of modules and who survived the selection pressures over the generations to learn their characteristic traits. In the case of long snakes, even though they tried to replicate the same sidewinding motion, they got easily tangled because of their long bodies. As in 6, we do not observe a constant number of joints across generations for maximum module 25, as compared to the other plots. One way of inferring this would be, as the number of joints increased, long bodies helped in covering more distance, but at the same time, the overall energy used by the robots increased. We also observed similar morphologies as in [10], of snakes with side limbs, as shown in 6 for stability and efficiency, despite exhibiting an atypical gait. For our experiments, this type of morphology showed more somersault behaviour. Here, we do not analyze the morphological behaviours of the robots, their stability, balance and gait, as our main focus in these experiments was to study the behavioural traits of energy efficiency along with an increasing number of joints.

7 Conclusion

Our investigation of the dependence of energy efficiency and the distance covered on the number of joints showed a positive relation. It is quite evitable, that longer robot bodies cover quite a distance with just little movement, but the servos of all the moving joints sum up to quite a lot of consumed energy. Nevertheless, observing how evolution navigates diverse constraints is a fascinating area of evolutionary robotics, forming the most optimal morphology for the best actions, further research can be done in this field of energy efficiency. Various values of thresholds for distance and energy used could be explored to see how the behaviour of the robots changes. Also, given that the evolutionary process is computationally challenging (based on longer run-times and multiple threads running simultaneously), robots with more joints, if simulated for considerably more generations could possibly learn a better and more efficient gait. Ongoing research could be done in improving the battery module to include other types of energy losses. Fine-tuning the PID controllers to mimic a more realistic scenario could also help in getting better results.

In conclusion, this study of energy-efficient robots have demonstrated the potential of evolutionary robotics as a powerful tool for designing and optimizing both the morphology and controller of a robot. By harnessing the principles of natural evolution, the evolving robots could learn, adapt and overcome obstacles to strengthen their advantageous traits in dynamic environments.

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