Novelty Search for Soft Robotic Space Exploration

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ABSTRACT

The use of soft robots in future space exploration is still a far fetched possibility, but it is too attractive not to be further researched upon. Soft robots are inherently compliant mechanisms that are well suited for locomotion on rough terrain or human-robot interactions. While obviously dependant on the particular application studied, scientists do not agree on what type of shape or locomotion strategy robots, and thus also soft robots, should have in order to be adapted optimally to an extra-planetary environment. Recent developments in soft robotics and evolutionary optimization showed the possibility to simultaneously evolve the morphology and locomotion strategy of certain type of soft robots. The use of techniques such as generative encoding and neural evolution were key to these findings. In this paper improve further on that methodology introducing the use of a novelty measure during the evolution process. We compare fitness search and novelty search in different gravity level and we consistently find novelty based search to perform as good as or better than a fitness based search, while also delivering a greater variety of designs. We propose a combination of the two techniques using fitness elitism in novelty search to obtain a further improvement. We then use our methodology to evolve the gait and morphology of soft robots at different gravity levels, finding a taxonomy of possible locomotion strategies that are analyzed in the context of space-exploration.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous

General Terms

Theory

Keywords

soft robotics, novelty search, CPPN, CPPN-NEAT, HyperNEAT, VoxCAD, space exploration

1. INTRODUCTION

Robotic exploration of extraterrestrial bodies is a challenging endeavour requiring the deployment of advanced technological solutions. The Huygens descent on Titan, the exciting landing of Philae on the comet 67P/Churyumov-Gerasimenko, the daily accounts of the three martian rovers Spirit, Opportunity and Curiosity are incredible missions that have gained us a great deal of new knowledge. One major challenge, in all of these missions, is mobility and, indeed, advanced mobility solutions for exoplanetary rovers are the subject of active studies. It is not uncommon, for these advanced concepts, to draw inspiration from biology as its the case of the Mars tumbleweed exploration concept [1, **?**], the lunar ALI exploration concept [**?**], or the many legged robots, inspired by insect locomotion, that are being studied by different scholars in the context of exoplanetary exploration. Typically, the locomotion strategy and the body morphology of a rover, though closely related, are not co-designed as they are treated as rather uncoupled entities. In reality, the best design for a rover will depend on the planet gravity, defining the entity of the contact forces to be used for locomotion, and on the complex interplay between gaits and rover body, which defines the stability and the performances of locomotion.

In this paper, we are interested in applying evolutionary techniques to evolve simultaneously the morphology and the gait of soft robots in different gravity environments. Given the extreme complexity of the task and the early research stages of the tools used, we are not interested in the actual final designs evolved, rather in their use to inspire future advanced robotic missions, as well as in improving upon previous work to contribute to the advancement of these techniques.

1.1 Soft Robots

Soft robotics is a highly promising field of research dedicated to the science and engineering of soft materials in mobile machines. As the name suggests soft robots [29, 19] are made entirely of soft materials mimicking animals or animal-parts that consist only of soft tissue (elephant trunk,

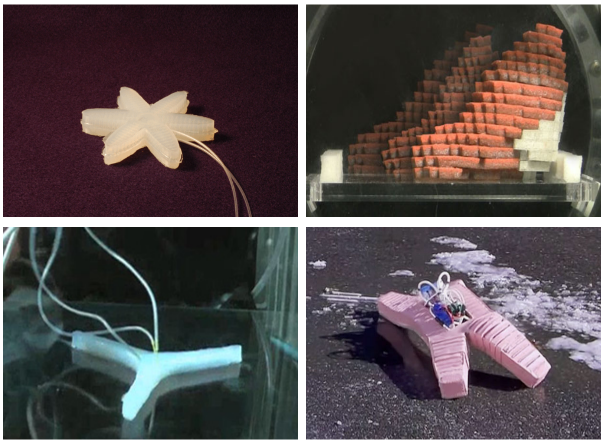


Figure 1: Soft robots can be actuated through air pressure tubes (top-left), pressure variations (top-right), or internal explosions (bottom-left). Autonomously actuated soft robot [28], it is able to withstand extreme temperatures and variant terrain types (Bottom-right).

tongue, worm, octopus, etc.). Having no rigid parts in their design the degrees of freedom are infinite and the possible ways of motion can become extremely complex. In traditional robotics, joints and rigid parts predefine the space of possible movement and sometimes restrict the robot's locomotion strategy or *gait* to a specific set. In soft robotics, the absence of rigid parts can on the one hand make the design of the locomotion strategy exceptionally tortuous, on the other hand the gait alternatives are limitless.

The actuation of such soft structures is the most challenging task. Actuating soft materials can be done in many ways including pneumatic systems [10, 23], hydraulic, internal body explosions, passive actuation triggered by pressure or temperature variations and others [12, 22]. Figure 1 illustrates four different ways that soft robot bodies can be actuated. Autonomously actuated soft robots [28] can also be designed having multiple advantages over rigid body robots such as resistance under extreme temperatures and the capability of locomotion on terrains of variant types.

1.2 Evolution of robotic locomotion

Evolutionary algorithms have been used to evolve the locomotion strategy of rigid and soft robots. Furthermore, the effects of gravity have been studied showing that it is possible to obtain a set of parameters to stabilize the gaits of a rigid robot under different levels of gravity.

Complex encoding representations such as artificial neural networks can control not only the morphology of rigid body parts connected with joints, but also control the forces applied to each joint. As a result, virtual creatures can be produced in a physical three-dimensional world [24]. Methods for evolving such virtual creatures like in [24] can utilize novelty search [16] and be far more explorative in the space of morphologies. Behavior novelty defined as a measure between morphological properties of the produced creatures driving the evolution to explore more diverse morphologies.

The effects of gravity on rigid robot gait evolution for space missions

The effects of gravity, slopes, and stiffness to the gaits achieved by a quadruped robot in dynamic walking and running have been researched [18, 11]. Furthermore, Hildebrand gait diagrams [5] are employed in analysing gaits resulting from an optimisation process according to criteria important for space missions, such as motion speed and energy efficiency. This study showed that it is possible to obtain stable gaits despite the varied conditions encountered in planetary exploration.

Evolution of soft robots

Considering soft robotics, topological optimization techniques can be applied to soft robots [8] for producing functionality in the design. Evolution of soft material robots as it was shown in [6], can result in soft robots able to produce locomotion. The possibility of evolving these soft structures using an indirect encoding was of interest to be exploited by [2]. A powerful generative encoding, CPPNs [26], was used to generate soft voxel-formed three-dimensional structures, coupled with the use of NEAT algorithm which ensures the increasing complexity of the networks produced. The superiority of this kind of generative encoding was verified against direct encoding, showing how CPPNs can take advantage of their geometrical properties. Evaluation was done by a simple displacement measure while evolution tended to evolve different kinds of locomotion strategies and morphologies as the fitness function was penalized for different parameters. An earlier work [9], apart from the generative encoding of CPPNs, made use of *Gaussian Mixture* and *Discrete Cosine Transform* to produce amorphous soft body structures. The simultaneous evolution of soft robot morphology and control was also investigated by recent work [20]. Some aspects of soft robot evolution were verified in this work, namely muscle placement and muscle-firing patterns can be evolved given a fixed body shape and fixed material properties. Furthermore, material properties can be co-evolved alongside locomotion strategies.

The present work builds upon previous work [2] making also use of novelty search to co-evolve the morphology and the locomotion capability of soft bodied virtual creatures. Pure novelty search failed to evolve fit solutions in previous work [16] used, it is of interest to apply and investigate its performance in virtual soft robots this time. We also investigate the effects of gravity in the evolution of soft robots morphology and locomotion strategy for the first time in the evolution of soft robotics.

2. BACKGROUND

2.1 VoxCAD simulator

Most work to simulate interactions and deformations within and between soft material bodies are mostly focused on the graphical part of the problem [3] sacrificing the accuracy of the simulation [27]. Three dimensional meshes [17] can represent these bodies including the dynamics of their materials. *VoxCad* simulator [7], is focusing mostly on the physics side of the soft material interactions not at the expense of a low frame rate simulating soft material deformations and interactions. A lattice is used within the simulator to represent the 3D workspace where voxels can be assigned different materials. Materials themselves are passive and cannot actuate without external trigger. The external force that can actuate the materials is the temperature of the environment.

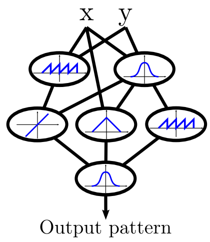


Figure 2: Compositional pattern-producing networks have identical network structure with artificial neural networks while they make use of a canonical set of activation functions.

Materials

Materials can be *passive* or *active* in respect to their reaction to the temperature changes. Passive materials do not react to temperature changes, while active materials expand and contract in respect to their thermal properties. Red and Green are the only actuated materials with non-zero and opposite thermal expansion coefficients. The two additional materials represent non-actuated tissue that can be soft (soft tissue) or hard (bones). Cyan voxels are soft having five times smaller elastic modulus of their material than Blue which have 50 MPa.

2.2 Compositional Pattern-Producing Networks

Compositional pattern-producing networks (CPPNs) [26] are artificial neural networks with an extended set of activation functions (see Fig. 2). This set of activation functions include repetitive, symmetrical, and linear functions. CPPNs can generate phenotypes that can be interpreted as distributions of points in a multidimensional Cartesian space, networks can then be queried in multiple resolutions.

For the purpose of this work, CPPNs are queried for every coordinate of the lattice space to form a soft robot morphology as well as, to define the distribution of the materials. The input nodes (neurons) of the CPPN are assigned to x, y, z normalized coordinates following [2], so that: $x, y, z \in [-1, 1]$. A bias input node is also introduced in the genome CPPN representation, this will allow the network to produce arbitrary outputs different from the defaults when all other inputs values are set to zero. More inputs can be added to the CPPNs, for instance the distance from the center point of the Cartesian phenotype space (lattice) as described in [26] and used in [2] which adds more bias towards symmetrical structures. The proposed input nodes for the three dimensions of the Cartesian space provide the minimum bias to the network outputs. Figure 3 illustrates the topology of a random CPPN network with the input and output nodes described earlier. The presence of a voxel in each coordinate of the lattice is determined by a single output of the CPPN, denoted with p while the selection of the material is determined by n-outputs.

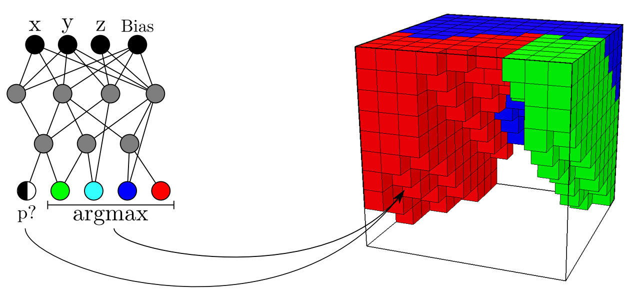


Figure 3: Each genotype (CPPN) is queried for every coordinate inside the lattice, its outputs determine the presence of a voxel and the type of its material.

2.3 CPPN-NEAT

Compositional pattern-producing networks as described earlier are similar computational methods to ANNs in regards to their structure, neuroevolutionary algorithms can be used to evolve CPPNs. NEAT [25] method can evolve CPPNs in the place of ANNs, since it only needs few modifications. The resulted method that evolves this generative type of genomes (CPPNs) is called CPPN-NEAT [26]. Previous work [2], showed that this method can indeed evolve the morphologies of the soft robots in the VoxCad simulation environment. *HyperNEAT*[1] is used for the implementation of the CPPN-NEAT algorithm.

3. METHODOLOGY

3.1 Novelty search

Novelty search [13, 15, 14, 21] unlike traditional fitness based search is an alternative way of optimization towards an objective function without having knowledge of this objective. What novelty search seeks for is how interesting a new solution is in respect to all previously found ones. To define "interesting" we need to move our point of interest into behavior space which is a function of each phenotype, similar to the fitness function. Nevertheless, it fully or partially describes the behavior without directly implying the fitness function. As an example someone can think of a behavior could be defined as the recorded trajectory of a robot which tries to maximize its velocity.

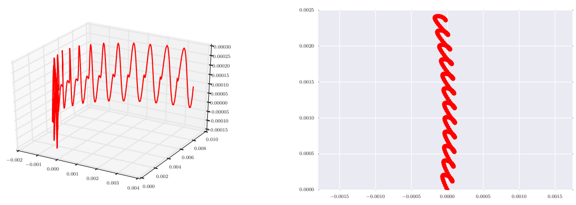
To define novelty, a metric measures the difference in the behavior space of the phenotype. Given the phenotype's behavior x a novelty measurement could be a function of x, $f(x)$ which computes how different (novel) is the specific behavior in respect to a set of other behaviors S in behavior space. As defined in [13, 15] *sparseness* can give a good measurement of how sparse is the area of a newly observed behavior. Given the behavior we can compute the sparseness by:

$$f(x) = \frac{1}{k} \sum_{i=1}^{k} dist(x, S_i) \tag{1}$$

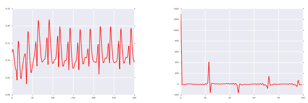
where S is a sorted set of the closest behaviors. Sparsity measures the average distance from the k-closest behaviors.

One significant point here is that the behavior space in some domains can be limitless. However, a valid behavioral metric can be found excluding behaviors that are meaningless or do not comply with the natural limits of the problem. On the other hand, the search space in the genotype level can also be infinite especially in neuroevolution methods like NEAT where ANNs can grow during the evolution. A bounded space of understandable-valid behaviors is then the key idea of novelty search where increasingly complex behaviors present to the evolution as the complexity of the genotype grows along.

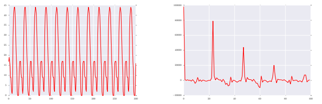
[1]HyperNEAT `v4.0 C++` by J. Gauci code (url: `https://github.com/MisterTea/HyperNEAT`)



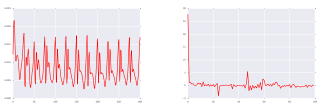
(a) Three and two dimensional trajectories of the soft robots.



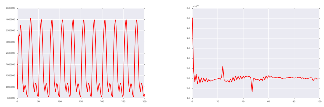
(b) Pace and discrete Fourier transformation of the the same signal.



(c) Voxels touching the ground and discrete Fourier transformation of the the same signal.



(d) Maximum pressure and discrete Fourier transformation of the the same signal.



(e) Kinetic energy and discrete Fourier transformation of the the same signal.

Figure 4: Observed behaviors of the soft robots used for the sparsity computation in novelty search.

Behaviours in Novelty Search

Regarding the evolution of soft robots in the specific simulated environment, a *behavior* can be defined as the way soft robots interact towards the environment. Every aspect of the soft robots movement that can be observed can be used to describe their behavior. Previous work [16] in a try to evolve walking three-dimensional virtual creatures used the evolved morphology of the creatures to describe their behavior. Although, comparing the morphology of the evolved soft robots is similar to comparing the chromosome (CPPN) of each individual. Behaviors that describe the morphology of the evolved robots have failed [16], since search is then forcing new types of morphologies without caring about the actual target of the evolution, which was the efficient locomotion. Therefore, only the comparison of the observed behavior in the phenotype level can lead the evolution towards more complex behaviors.

It is expected that behaviors that contain information about the goodness (displacement) of individuals will be more successful than behaviors that include other aspects of the soft robots' behavior. Figure 4 presents all the behavior types used for the novelty metric computation. For all recorder behavior metrics a constant sampling rate ensures that all signals have the same length. The behaviors designed to describe the strategy and the efficiency of the evolved locomotion strategies. They contain information that indirectly implies both the objectives of the evolution. *Trajectories* (2D and 3D), incorporate all the needed information such as speed, displacement, and locomotion strategy. To avert from same trajectories in all possible directions trajectories are normalized, meaning that their starting coordinates are always the start of the axes ($< 0, 0, 0 >$) and the point coordinates of the trajectory are rotated so their center of mass is normalized to a specific angle ($\theta = 90^o$). To measure the difference of two trajectories the Euclidean distances between coordinates at the same sampling time are measured, so that:

$$\text{i-trajectory: } t_i = t_i^1, t_i^2, \ldots, t_i^N \tag{2}$$

$$\text{j-trajectory: } t_j = t_j^1, t_j^2, \ldots, t_j^N \tag{3}$$

$$\text{Difference: } t_i - t_j = \sum_{n=1}^{N} dist(t_i^n, t_j^n) \tag{4}$$

where n is the number of sampled coordinate points and *dist* is the Euclidean distance. Apart from trajectory type behaviors, pace, voxels touching the ground, kinetic energy, pressure, as well as, the discrete Fourier transformation of these signals were used to define other behavior types. The similarity or the difference of two of the same type behaviors can be determined by the equations provided while these measures of difference are used by the sparsity equation (see Eq. 1) to compute the sparseness of a given behavior in the behavior space. Individuals with novel observed behaviors (high sparseness value) are then stored in a list helping the evolution to avoid generating similar behaviors.

3.2 Fitness Elitism in Novelty Search

Elitism is the process of passing mutations or copies of the best individuals to the next generation. The best individuals of each species generation are protected so they can contribute with their beneficial genes later in the evolution. Novelty search can include elitism in its selection process, and it does that by copying the most novel organisms of the current population of each species to the next while the same function can also be used to copy fit individuals within novelty search method. The way these two elitism functions can be combined together depends on the population size and the problem, while probabilistic methods can also be applied. In the specific setting, both elitism function copy new individuals to the new generation with probability one. Moreover, evolution towards novelty does not get disturbed, at the same time fit individuals have the chance to be optimized further as long as they are the fittest within the species population.

3.3 Experimental setup

Each experiment consists of 10 runs under the same settings. As in [2] and for comparison purposes a population of 30 on each generation is used, the maximum number of generations in the evolution is set to 1000. Due to computationally expensive simulations, not all experiments are performed using a lattice resolution of 10^3, resolutions lower than 10^3 are used as well. More specifically, $5^3, 7^3, 10^3$ lattice resolutions are used. All settings regarding CPPN-NEAT algorithm are the same as in [2].

4. RESULTS

Pure novelty search is compared in respect to the goodness measure used in the simulations (displacement of soft robots in body-lengths) to fitness based search. Different behavior types are used to investigate the effects on performance of novelty search method. Elitism is used in a proposed methodology to incorporate fitness information in novelty search. Last, the performance of both methods are investigated for several levels of gravity. Furthermore, evolved locomotion strategies under different gravity conditions show how environmental conditions can affect the evolved morphologies and the locomotion strategies of soft robots.

4.1 Behavior selection

Figure 5 illustrates the performance achieved by novelty search for 10 behavior types. What is shown is the fitness in body lengths of the champion soft robot of the whole evolution from 10-independent runs. Both trajectory-type behaviors achieve the best performance in regards to the fitness measure, with a small difference in favor of two-dimensional over three-dimensional trajectories. The rest of the behavior metrics apart from VTG and DFT-VTG are close as far as the final performance of the evolution is concerned. One reason they fail to meet the trajectories' performance is the fact that although they keep track of cues that can describe the performance of the robot (speed/displacement), they cannot encode the direction of them. Soft robots having a circle trajectory can produce fast locomotion, in this case though, the measured displacement from their initial position remains low. Counting the number of voxels of a soft robot that touched the ground in every sampling timestep of the simulation, does not imply how fast the robot is moving. A fast moving robot that is hopping can have a similar behavior with a hopping robot that stays in the same position. On the contrary, using the trajectories of these two soft robots, the behaviors observed would have been highly variant.

4.2 Performance Comparison

To compare the performance achieved by novelty search method, its performance is set side by side with fitness based search (normalized body-length displacement of the soft robot's center of mass from its initial position), random search, and finally a simple genetic algorithm[2] with direct encoded genomes. The same experiment held under two different simulation settings (for resolutions 5^3 and 10^3). Notice, that the first three methods are referring to a generative encoding (CPPNs) evolved by CPPN-NEAT evolutionary algorithm and using selection in respect to novelty, fitness, and random selection. The last method uses a direct encoded genome driven by fitness within a simple genetic algorithm. Two dimensional trajectories are used by novelty search in order to describe the novelty in the behavior space through sparsity equation.

Figure 6 presents the results for the low resolution soft robots (5^3). The average best displacement so far is presented alongside the deviation error. Notice, the difference between novelty search and the other methods. Using the two-dimensional trajectories of the soft robots, novelty search visits optimal solutions that none of the other methods does. Local optima can prevent fitness based search to achieve the performance of novelty search. Encoding limitations in direct encoding cannot lead to optimal solutions for this settings. In the case of random search, having neither the information about their fitness, nor the driving force of novelty search that seeks for novel behaviors, it fails to evolve any decent locomotion. The only reason random search in CPPN-NEAT achieves to evolve displacement of ~ 5 body-lengths, is the powerful encoding used (CPPNs). The simple genetic algorithm approach performs better than using random selection with an indirect encoding. Structural regularity do not show all of their advantages in such low resolution settings.

In higher resolution lattices, it is expected that generative encoding will prove its merits over the direct encoding scheme [2, 26]. More complicated morphologies can be produced (morphology space for 10^3 lattice resolution: 9.3×10^{698}). Furthermore, the space of behaviors, for instance two-dimensional trajectories, becomes larger since more complex soft robots can achieve higher displacement and more advanced strategies for locomotion. As it has been shown before, these higher resolution morphologies can achieve life-like locomotion. Figure 7 illustrates the performance (i.e best displacement so far) of the four different methods in these higher resolution settings. Results reassure that novelty search achieves higher fitness ($>$ 1-bodylength) on average against fitness based search. Nevertheless, there is no tremendous difference as in the previous experiment. Both methods achieve to evolve the soft robot structure with the highest fitness found in all experiments ($\sim$ 14 Body lengths). Novelty search behaves more constant in evolving individuals with high fitness in all runs, on the other hand

[2]The GAlib C++ library [30] used for the implementation of this method. Source code used from [2].

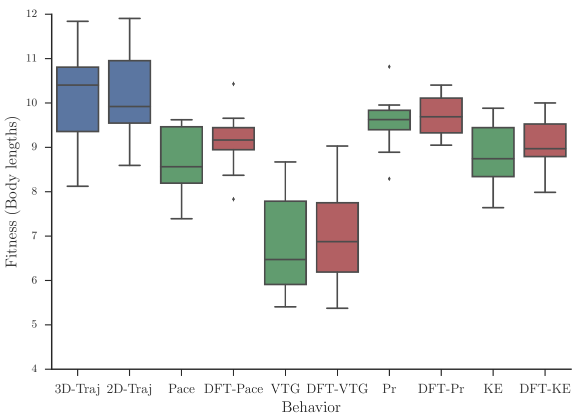


Figure 5: Distributions of the champion fitness under 10 variant defined behaviors for novelty search. Blue are trajectory type behaviors (3D and 2D), Green are 1D signals (Pace, Voxels touvhing the ground (VTG), Pressure (Pr), and Kinetic energy (KE)). Red is the discrete Fourier transformation of these 1D signals.

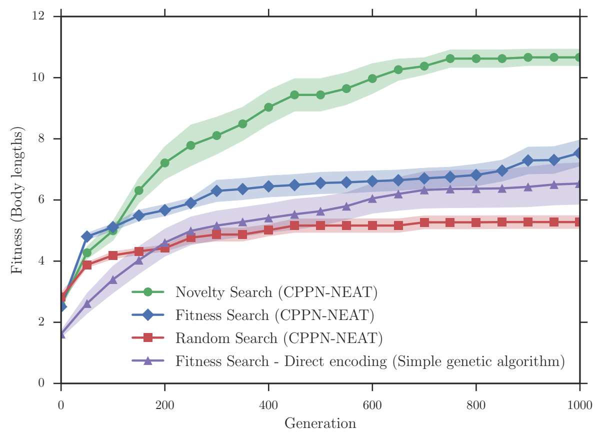


Figure 6: Comparison of simple genetic algorithm (direct encoding) against novelty-fitness-random search with generative encoding. Best fitness so far averaged over 10 runs.

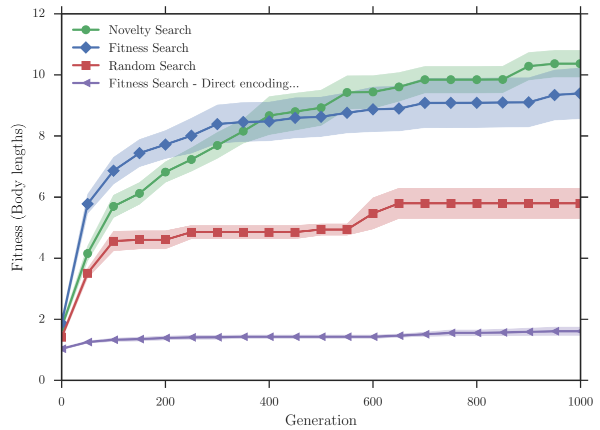


Figure 7: Comparison of simple genetic algorithm (direct encoding) against novelty-fitness-random search with generative encoding. Best fitness so far averaged over 10 runs.

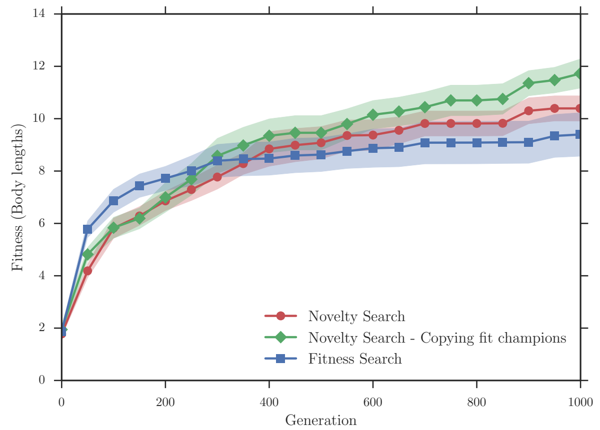


Figure 8: Best fitness so far, novelty search with and without copying *fit* champions (Fitness Elitism), and fitness search, averaged over 10 runs.

most of individual runs of fitness search are being trapped in low fitness local optima, trying to optimize specific individuals without trying to explore deeply the fitness landscape like novelty search successfully does. The high difference between random evolution and novelty search proves that seeking novel behaviors in novelty search cannot be considered as a random search. The superiority of generative encoding (CPPN) over direct encoding can be evidently observed. Regular in shape morphologies can take advantage of their geometrical properties to move efficiently.

4.3 Fitness Elitism in Novelty Search

The reason that novelty search is considered such a revolutionary search method is because it finds solutions for deceptive problems, where the fitness landscape is not a straightforward function. On each generation of novelty search novel behaviors that are also fit in regards to the objective of the problem are discovered. Mutations of these solutions will yield in behaving similarly to their ancestors, resulting in similar behaviors. Thus, the novelty value of these individuals will be declined as similar behaviors will contribute in a denser area in the behavior space. Eventually, these solutions will stop being selected, and evolution will not have the chance of carrying their genes along. Mutations and other genetic operations can optimize these fit individuals more. These individuals (with high fitness value) can be seen as *stepping stones* [15] towards more optimized versions of themselves. Being blind to the objective function, novelty search will eventually stop producing new individuals out of them, which will lead to promising individuals being unable to survive through the evolution process. Figure 8 illustrates the gain in performance when fitness elitism is used in novelty search method compared with the pure novelty and fitness based search methods.

5. EVOLVING SOFT ROBOTS FOR OUTER SPACE

Gravity conditions can affect the evolution of soft robots. Both methods discussed, novelty and fitness based search, are used for the co-evolution of the morphology and the locomotion strategy of soft robots under variant gravity levels. For the novelty search method two-dimensional trajectories of the soft bodies are chosen as the behavior metric to evaluate the novelty of each individual. Figure 9 presents the performance of novelty and fitness based search for four different gravity levels under a lower resolution setting of 7^3.

Robots on Lunar

Locomotion strategies evolved under low gravity conditions for the gravity of the Lunar more specifically, showed that only hopping gaits can produce effective locomotion. Low gravity makes it difficult for the soft body structures to grip on the ground surface and evolve different strategies than hopping. The morphology of each hopper differs. A C-shaped hopper soft robot (see Fig. 10a) evolved in these settings.

Soft Robots on Mars

The locomotion effectiveness on Mars is higher when is compared to this on Lunar's gravity acceleration making it possible for the virtual soft robots to evolve other kind of gaits using legged bodies (see Fig. 10b). Note that the C-shaped hopper soft robot mostly uses passive materials apart from

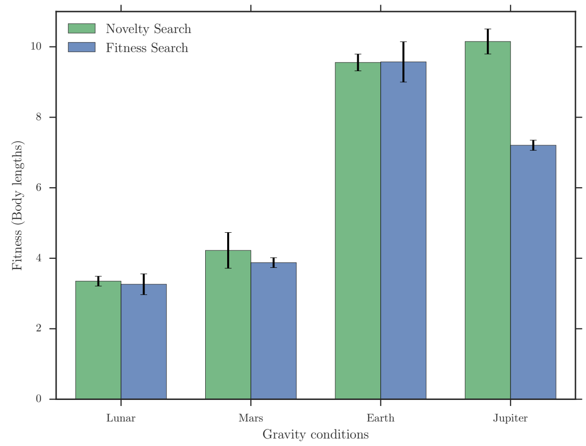
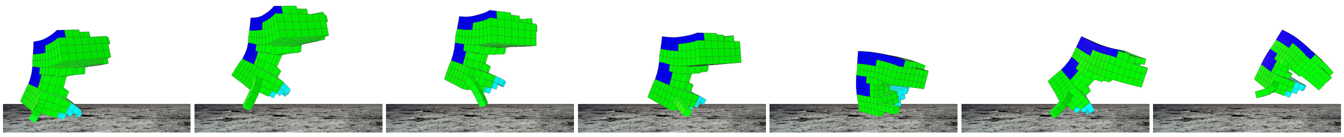
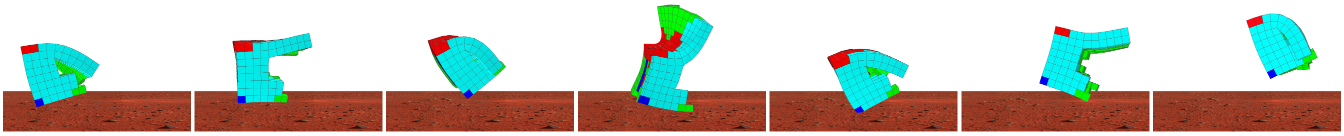


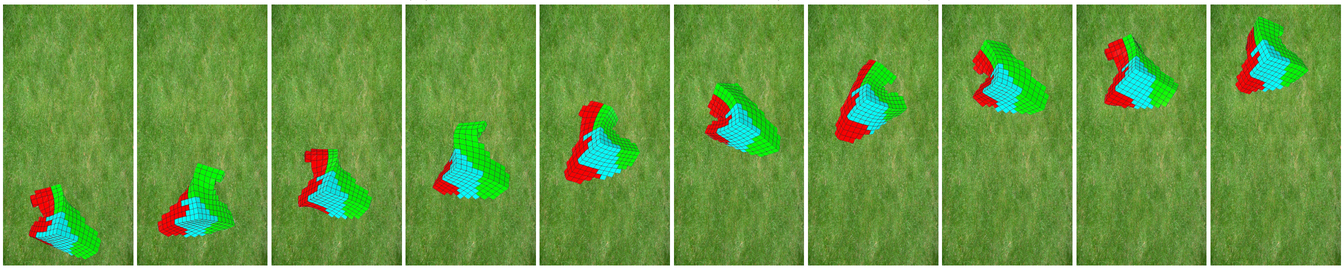
Figure 9: Novelty search performs better or equally good than fitness based search in all gravity conditions tested.



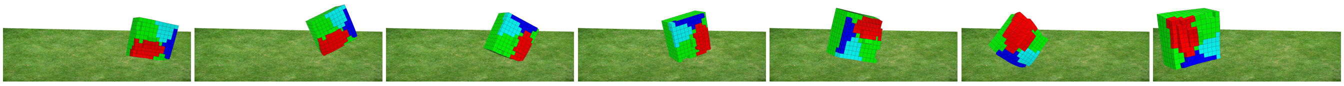
(a) **Lunar** C-shaped hopper (Novelty-Search)



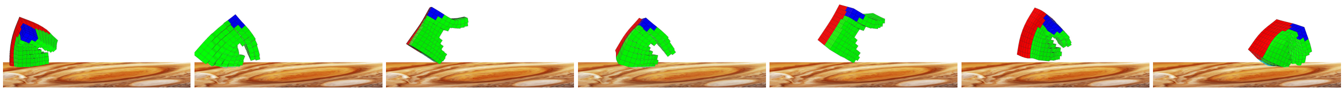
(b) **Mars** 2-legged C-shaped hopper (Novelty-Search)



(c) **Earth** *Top view*, 4-legged animal like locomotion (Fitness-Search)



(d) **Earth** Tumbleweed-like locomotion (Novelty-Search)



(e) **Jupiter** (Assuming a stable surface) C-shaped hopper (Novelty-Search)

Figure 10: Locomotion strategies evolved in variant gravity conditions.

its upper body where all the active material are located. With using its upper part generates enough motion able to move itself. What is observed in the morphologies of soft robots evolved in lower gravity levels was that the use of less number of active voxels can produce decent locomotion.

Soft Robots on Earth

On higher gravity levels life-like locomotion emerges. Interesting animal-like gait has been evolved (see Fig. 10c) verifying the connection there is between gravity and the locomotion strategies of living organisms evolving on Earth for thousands of years. Tumbleweed-like locomotion (see Fig. 10d) has been emerged under novelty search method producing rolling soft robots that can locomote efficiently. Fact that adds significance to the novelty search method since fitness based search did not produce this kind of locomotion strategy. Tumbleweed is a concept of low-cost exploration that has inspired robot designers for Mars' missions in the past [1] and has been already deployed in Antarctica for testing purposes by NASA.

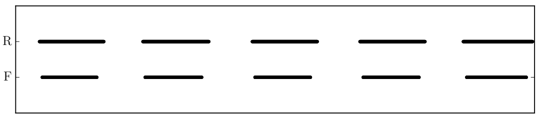
Soft Robots on Jupiter

Moving on to higher gravity levels, Jupiter, heavier structures can use galloping as a strategy for their locomotion. Galloping is again considered to be an effective way of moving in such a high gravity, whereas thicker legs are evolved to withstand the high gravitational force. Push-pull worm-like locomotion can also produce decent velocities for soft robots. Finally, hoppers have also been evolved to this setting, while they are using more actuated materials (see Fig. 10e).

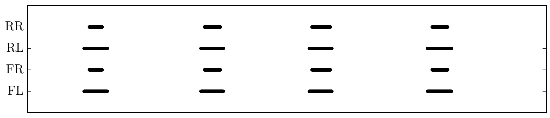
Different locomotion strategies can be evolved on different gravity levels producing effective locomotion. Low gravity does not allow other kinds of locomotion apart from hoppers to be evolved, while higher gravity acceleration allows more complicated behaviors to be evolved. In all settings, both search methods produced effective locomotion for the soft body structures, however, the performance in regard to the objective measure defined, displacement of the body in body lengths, was equal or higher for novelty search in all gravity settings.

6. DISCUSSION

It has been shown how with the use of a predefined set of materials and a generative representation for the morphology of soft robots, efficient locomotion can be achieved under different gravity levels. As it was shown by the evolution of a rolling tumbleweed-like [1] soft robot, this work can inspire the robotic design of future comet or planetary exploration robotic missions. Extreme temperature fluctuations especially on Comets can trigger passive actuated materials to perform a designed movement. Although the simulator used cannot simulate extreme variations that happen on Comets, we believe that a form of passive actuated probe-parts could have saved Philae [?], the robotic-probe landed on comet 67P.



(a) Two legged soft robot.



(b) Four legged soft robot.

Figure 11: Hildebrand diagrams of two evolved soft robots for Earth's gravity acceleration. Timing of impacts between its legs and the ground.

7. FUTURE WORK

Different behavior types defined in this paper in regards to the computation of the novelty measure for a individual behavior. To achieve novelty in the locomotion strategy of an evolved soft robots can be done also by combining two or more behavior metrics, a linear combination of the novelty values in more than one behavior levels can be then used to define the novelty of a soft robot. Hildebrand diagrams as shown in Figure 11 (Diagrams are shown for two of the evolved soft robots on Earth) can also be used a different behavior, as they have been used to describe the locomotion pattern of animals or legged robots. Experiments under different levels of gravity and the frequency of the temperature, showed that there is a clear connection between the frequency of the temperature variation and the gravity which was not in the scope of this work. The chromosome of the evolutionary process can also include the frequency of the actuation as an evolved variable which can then be applied to autonomously actuated soft robotics on different gravity levels.

8. CONCLUSIONS

For the first time in evolutionary soft robotics a diversity based method such as novelty search was used. Novelty search method outperformed traditional fitness based search in evolving soft robots morphologies under the same objective which was the normalized by body-length displacement of soft robots. Previous work in evolving virtual creatures by novelty search [16] used the resulted morphology of the robots created to determine the novelty of an individual. The resulted performance for pure novelty search method was worse than the fitness based. On the contrary, well defined behavior metrics can lead novelty search to outperform traditional fitness based search used in [2]. Novelty search not only improved the performance and the diversity in the behavior space, but also contributed to a larger variety of virtual creatures evolved. Incorporating fitness information in novelty search resulted in a significant performance gain over pure novelty search method. Finally, both techniques were used to evolve soft robots in four variant gravity levels, showing interesting results and the possibility of influencing future robotic designs for planetary exploration.

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