

Fusing Novelty and Surprise for Evolving Robot Morphologies

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ABSTRACT

Traditional evolutionary algorithms tend to converge to a single good solution, which can limit their chance of discovering more diverse and creative outcomes. Divergent search, on the other hand, aims to counter convergence to local optima by avoiding selection pressure towards the objective. Forms of divergent search such as novelty or surprise search have proven to be beneficial for both the efficiency and the variety of the solutions obtained in deceptive tasks. Importantly for this paper, early results in maze navigation have shown that combining novelty and surprise search yields an even more effective search strategy due to their orthogonal nature. Motivated by the largely unexplored potential of coupling novelty and surprise as a search strategy, in this paper we investigate how fusing the two can affect the evolution of soft robot morphologies. We test the capacity of the combined search strategy against objective, novelty, and surprise search, by comparing their efficiency and robustness, and the variety of robots they evolve. Our key results demonstrate that novelty-surprise search is generally more efficient and robust across eight different resolutions. Further, surprise search explores the space of robot morphologies more broadly than any other algorithm examined.

CCS CONCEPTS

• **Computing methodologies** → **Search methodologies; Genetic algorithms; Evolutionary robotics;**

KEYWORDS

Surprise search; novelty search; divergent search; deception; evolutionary robotics; soft robots; CPPN; artificial life

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1 INTRODUCTION

Evolving virtual creatures has been a popular domain for testing the creative capacity of evolutionary algorithms (EAs). The primary

objective of EAs in this domain is to evolve and discover morphologies that will move robots as far as possible within a given simulation period. Over the years several environments have been proposed to serve this purpose, ranging from evolving rigid bodies [18, 26] to soft body morphologies [12]. While it has been feasible for EAs to evolve efficient artificial creatures that behave (i.e. move) in unconventional ways, the obtained phenotypes still fall short when compared to the behavioral complexity met in nature. In an attempt to allow EAs to reach higher levels of evolved complexity, Cheney et al. [2] proposed the evolution of different materials within the creatures' morphologies. Inspired by the different tissue forms we meet in natural morphologies 'soft' robots are composed of voxels with different properties. Such robots are equipped with higher degrees of freedom that allow them to explore more diverse movement strategies.

It is evident that the complexity of soft robot evolution can leverage the creative capacity of EAs and directly affect the design space and the expressivity of solutions. In that regard, the design of an appropriate reward system is critical for obtaining highly fit solutions within this domain [18]. It is only expected, however, that local optima existent in the fitness landscape can strongly bias search towards less effective morphologies [15]. Moreover, by explicitly rewarding solutions in terms of their goodness we may deter the discovery of unconventional yet efficient behaviors [4]; this is normally due to the tendency of traditional EAs to converge to a single good solution. As a response to this limitation, a recent trend in evolutionary computation (EC) is inspired by open-ended evolution [31] and focuses on rewarding behavioral characteristics of obtained solutions such as the degree of *divergence* among them. By ignoring the objective and instead rewarding behavioral diversity we can tackle the premature convergence of EAs typically encountered in evolutionary robotics [23, 25].

Being a popular example of a *divergent search* algorithm, *novelty search* is an open-ended EA that does not consider the objectives of the problem explicitly but instead searches for novel solutions in the behavioral space [17]. The recently introduced *surprise search* algorithm [7, 32] is also built on the principles of open-ended evolution and rewards *unexpected* behaviors throughout the evolutionary process. While novelty search (NS) and surprise search (SS) have demonstrated their effectiveness independently across several benchmarks [7, 9, 10, 17], it was only very recently that the two were coupled and tested for evolutionary divergence in maze navigation [8].

Based on the promising findings of [8] our hypothesis in this paper is that coupling novelty and surprise is a necessary condition for discovering even more highly-performing and unconventional solutions in the search space of virtual creatures. Even though novelty-surprise search—as the algorithm that combines novelty and surprise rewards has been named—has been tested already in

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maze navigation tasks [8], there has not been sufficient exploration regarding its performance in more challenging domains with more complex behavior characterizations. In that regard, evolving a soft robot morphology is a suitable domain that offers complexity with respect to the task per se but also with respect to behavior characterization. On the one hand, it is a complex problem that allows for many different configurations of materials, especially when the resolution of the 3D lattice in which these materials can be placed increases [29]. On the other hand, behavioral diversity in soft robots can be measured in a more granular fashion than e.g. in maze navigation, via the entire trajectory of the robot during simulation.

This paper tests how novelty search, surprise search, and novelty-surprise search perform in the domain of soft robot evolution in terms of efficiency and robustness. The performance of these divergent search approaches in finding individuals which can reach distant points in a 3D simulation is compared with traditional fitness-based search towards that very objective. All algorithms in this paper are tested across eight different soft robot setups, with varying lattice resolution, allowing for a comprehensive assessment of their efficiency and robustness. Our key findings reveal that coupling novelty and surprise is a beneficial search strategy with regards to both algorithmic efficiency and robustness when compared against all other algorithms. Further, we put an emphasis on the different ways each algorithm explores possible robot structures and we observe that surprise search and novelty search favor very different morphologies. It also appears that the structural diversity of robots evolved by surprise search is significantly higher than that of all other approaches tested.

2 BACKGROUND

This section reviews methods for divergent search and the domain of soft robot evolution.

2.1 Divergent Search

Divergent search is a recent paradigm that pushes for the intrinsic properties of search [17], instead of rewarding directly a solution's proximity to an objective. This paradigm has been introduced to counter the effects of a *deceptive* landscape. A deceptive fitness landscape challenges the discovery of a global optimum for traditional evolutionary computation, as the local optima may guide the search away from it [4]. To counter this behavior, several approaches have been proposed over the years, such as speciation and niching, in order to preserve solution diversity [20]. While these techniques try to push for genotypical diversity, open-ended evolution handles deceptiveness in the behavioral space.

2.1.1 Novelty Search: While traditional evolutionary search rewards explicitly the objective of the problem, novelty search [17] pushes for divergent behaviors by ignoring the fitness of the problem it attempts to solve. This algorithm selects individuals based on how different the solutions found are compared to the current population and an archive of past novel individuals. In every generation, individuals may be added to the archive if their novelty score is above a dynamic threshold. Novelty search is able to explore uncharted areas of the search space, as it is neither random nor exhaustive search [17, 21, 22, 30]. The novelty score $n(i)$ of an

individual i is evaluated based on the average distance (d_n) of the n nearest neighbors in the current population and the novel archive:

$$n(i) = \frac{1}{n} \sum_{j=0}^n d_n(i, j), \quad (1)$$

where j is the j -th nearest neighbor to i based on the distance d_n (which is problem-dependent).

2.1.2 Surprise Search: While novelty search pushes for *novel* behaviors, surprise search is an alternative divergent search algorithm that rewards *unexpected* behaviors. Surprise search uses a prediction model to identify behavioral patterns in previous generations and predict behaviors in the current generation; following that, it rewards behaviors that deviate from the predicted ones [6, 32]. Therefore surprise search attempts to mimic a self-surprise process [5] that is built upon the behaviors evolved in the past generations. The prediction space becomes the new search space for the algorithm, which can be different from the behavioral space. The prediction space is in general agnostic of the physical constraints of the simulation: for example, if an obstacle is present in the simulation scene, the predicted path might traverse that obstacle.

Surprise search consists of two key phases: the prediction phase (Eq. 2) and the deviation phase (Eq. 3). In the first phase, the algorithm tries to predict the behaviors of the current generation, based on a number of past generations (h in Eq. 2) and the locality of the behavioral information (k in Eq. 2). These two pieces of information are used to build the prediction model m :

$$\mathbf{p} = m(h, k). \quad (2)$$

Once the predicted behaviors \mathbf{p} (of size k) are found, the algorithm rewards unexpectedness in an individual based on its distance from the n closest predicted behaviors of the current generation:

$$s(i) = \frac{1}{n} \sum_{j=0}^n d_s(i, p_{i,j}), \quad (3)$$

where $s(i)$ is the surprise score assigned to individual i , computed as the average distance d_s of i from its n closest predictions ($p_{i,j}$). This formula considers the prediction space, rather than the distance between the current and past trends of the population as e.g. captured by Eq. (1).

2.1.3 Novelty-Surprise Search: Novelty and surprise reward different behaviors, and one can argue that the notions of novelty and unexpectedness are orthogonal. Inspired by this theoretical distinction, [8] introduced a fusion of novelty search and surprise search which combines the two rewards linearly. Novelty-surprise search (NSS) combines the two rewards: $n(i)$ from Eq. (1) and $s(i)$ from Eq. (3). Unlike surprise search, NSS maintains an archive of novel individuals for the purposes of calculating the novelty reward. The impact of each reward is controlled by a single parameter λ :

$$ns(i) = \lambda \cdot n(i) + (1 - \lambda) \cdot s(i), \quad (4)$$

where $ns(i)$ is the combined novelty and surprise score of individual i and $\lambda \in [0, 1]$ is a parameter that controls the relative importance of novelty versus surprise.

This algorithm has been shown to be more efficient in maze navigation tasks [8] than both surprise search and novelty search

on their own. However, the behavior characterization for maze navigation was merely one point in a 2D space (i.e. the final position of the robot at the end of simulation). This paper, on the other hand, tests the capabilities of NSS in a more complex scenario, which involves a multidimensional behavior characterization; i.e. the trails of the robots throughout the simulation. Our main hypothesis in this paper is that the combined push towards both novelty and unexpectedness can evolve soft robots with better performance in terms of efficiency and robustness. For this purpose we test our hypothesis across different search spaces; i.e. across various levels of complexity for the morphology of soft robots.

2.2 Soft Robot Evolution

The domain of evolutionary robotics traditionally focuses on artificially evolving the structures of virtual creatures. The robots' numerous degrees of freedom and the difficulty of the task makes EC ideal for tackling this problem. Previous work has focused on evolving rigid bodies [18, 26], as they are simpler and less computationally expensive to simulate. On the one hand, the few degrees of freedom can limit the dexterity of rigid bodies, unless an excessive number of joints is used. On the other hand, soft bodies have a distributed deformation that permits theoretically infinite degrees of freedom, allowing these “soft” robots to reach any point in the space with an infinite number of configurations. Moreover, soft bodies can conform to obstacles, as they generate little resistance to external forces [29].

Relatively few attempts have been made to evolve soft robots, as this problem comes with a high computational cost in simulating these materials and a large parameter space, especially if different materials are applied. Hiller and Lipson introduced the use of a soft-voxel simulator (VoxCad) to simulate the statics and the dynamics of soft bodies within reasonable computational budgets [11]. The lattice of the soft robot has a predefined resolution, and multiple materials are chosen as building blocks to compose the robot, both active (as they can contract and expand following an external signal) and passive (e.g. not actuated).

Within the domain of evolving virtual creature morphologies, it has been shown that direct encodings tend to lead to poorly structured and dysfunctional robot architectures [2]. For that purpose, several indirect encodings have been proposed, including L-systems [13], hierarchical nested graphs [26], and gene regulatory networks [1]. In [2], Cheney et al. propose to evolve soft morphologies by evolving Compositional Pattern Producing Networks (CPPNs) [27], given their high evolvability and expressive range capacities. A CPPN is an artificial neural network with nodes of different activation functions (sine, sigmoid, Gaussian, etc.) which allow regularities, repetitions and other patterns to emerge [27]. CPPNs evolve using the neuroevolution of augmenting topologies (NEAT) algorithm, which starts from simple networks and complexifies them via recombination and mutation over the course of evolution [28]. NEAT uses speciation to limit competition between very different network structures. As shown in [2], the CPPN representation allows soft robots to exhibit several locomotion strategies and morphologies.

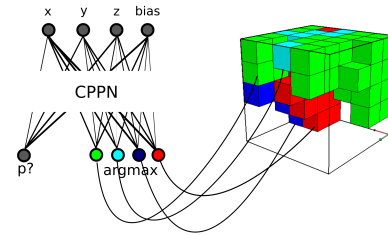


Figure 1: A CPPN describes the materials of a 5×5×5 lattice.

Previous work in soft robot evolution has focused on a single reward, which is either the distance covered, the novelty or surprise of the evolved behaviors [2, 7, 9, 16, 18, 23, 26]. In this work, we extend previous work on exploring divergent approaches in artificial life [9, 23] by combining two algorithms, novelty search and surprise search [8]. We compare the performances of four algorithms across different resolutions of lattices and we perform an analysis of the structures favored by each approach.

3 DOMAIN

This paper evaluates the outcomes of soft robot evolution in terms of efficiency, robustness and structural diversity. The goal is to assess how divergence can affect the quality of the outcome and investigate the emerging differences between the robot structures favored by each EC approach. The evaluation is based on data collected through simulations run on VoxCad [11], which simulates the statics, dynamics and non-linear deformation of heterogeneous soft materials quantitatively. The simulation framework can reproduce several materials, both active (volumetric actuated materials) and passive (for example soft and hard tissue with different stiffness). Following [2], soft robots consist of four materials, two active (red and green) and two passive (cyan and blue). Green voxels expand and contract following a signal at a predefined frequency, while a counter-phase signal actuates the red voxels. Passive materials are not actuated but are deformed by nearby materials: cyan voxels are soft (low stiffness), while blue voxels are harder and stiffer. These voxels are placed on a 3D lattice with a predefined resolution; the evolved morphologies are simulated via VoxCad [11] and the resulting behavior is used to compute the fitness of the evolved robot. As in [2], a CPPN is used to determine the material (if any) of each voxel. Each x, y, z coordinate of the cubic lattice is provided as input to the CPPN: its first output determines whether the voxel is empty, while the highest score of the remaining four outputs decides the material of that voxel (see Figure 1).

Four different EC approaches are tested in this paper: three divergent search algorithms and the objective-driven search as a baseline. To compare the algorithms in terms of performance (in Sections 4.2 and 4.3), the fittest individuals in each of 90 independent runs are collected. Further, the structural diversity of the obtained robots is analyzed in Section 4.4 based on the 90 populations evolved during 1000 generations by each algorithm, to test their ability to explore different morphologies throughout evolution.

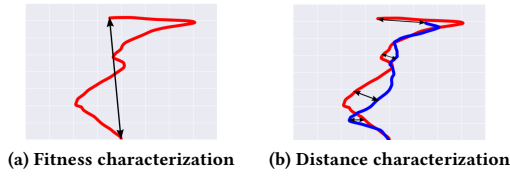


Figure 2: Behavior characterization for (a) objective search as the Euclidean distance between the starting and the ending point and (b) divergent search as the average distance of two trajectories sampled at the same rate.

3.1 Objective Search

In fitness-based search, the objective is to evolve robots capable of moving as far away as possible from a fixed starting point. Based on [2, 23], the chosen performance metric is the Euclidean distance of the robot's center of mass between the start and the end of simulation time in body lengths (see Figure 2a). Objective search (OS) attempts to maximize this distance.

3.2 Divergent Search

Divergent algorithms such as novelty, surprise and novelty-surprise search require a different behavior characterization in order to compute the distance between individuals, via $d_n(i, j)$ in Eq. (1) and $d_s(i, j)$ in Eq. (3). Several behavior characterizations have been explored in [23], such as the number of voxels touching the ground, kinetic energy or pressure. A straightforward behavior characterization is the trajectory of the soft robot during simulation, which is directly correlated with the robot's displacement. The two-dimensional trajectory¹ of the soft robots has proved to be best in achieving good performance with novelty search [23]. For a fair comparison between the three divergent approaches, the distance characterization for both novelty and surprise is the average of the Euclidean distance between sampled points of two trajectories $r_{i,s}$ and $r_{j,s}$ (see Eq. 5 and Fig. 2b). All trajectories start at the same point and are sampled at a fixed rate, which guarantees a behavior with a fixed length. Moreover, all trajectories are transformed to make the computed measures rotation invariant, i.e. all points are rotated so that the average overall path points fall on the x -axis, as in [23].

$$dist(i, j) = \sum_{s=1}^S \|r_{i,s} - r_{j,s}\|, \quad (5)$$

where $r_{i,s}$ is the position of the robot i at the simulation step s . S is the total number of samples considered during the simulation.

3.2.1 Novelty Search: Novelty search (NS) uses the parameters of [23]; the novelty score is computed as the average distance of 10 nearest neighbors, i.e. $n = 10$ in Eq. (1), using Eq. (5) for d_n . Novelty search makes use of a novelty archive, where the most novel individuals in each generation are stored.

3.2.2 Surprise Search: As described in Section 2.1.2, surprise search (SS) relies on a prediction model and a distance function.

¹The three-dimensional trajectory of the robot is simplified by ignoring the height (z) component.

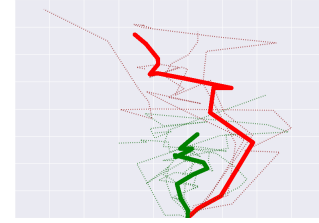


Figure 3: Visualization of the k -means calculation for surprise search: the thick red and green lines are, respectively, two example centroid trajectories obtained by clustering the dotted red and dotted green robot trajectories.



Figure 4: The key phases of the surprise search algorithm. Surprise search uses a history of two generations ($h = 2$) and 15 clusters ($k = 15$) in this example. The example centroid of a cluster of trajectories in this example is a trajectory depicted as a red line in generation $t-2$ in this example (a). The centroid trajectory of $t-1$ (b) and the prediction of the trajectory for generation t (c) are depicted as dark red and blue lines, respectively.

The surprise score is computed as the average distance between the individual's trajectory and the n closest predicted trajectories. The predicted trajectories are computed via linear regression of the sampled points of the previous two generations ($h = 2$ in Eq. (3)). The local behaviors are computed via k -means clustering: this algorithm computes the local behaviors by finding k centroids of the robot trajectories, by using the distance measure detailed in Eq. (5). Fig. 3 shows how k -means finds two centroids from trajectories sampled at the same rate: as an example, the green thick line is a sequence of centroid points computed by averaging the trajectories assigned to the green cluster. In this paper $k = 15$ and $n = 4$ in Eq. (2) and Eq. (3) respectively, found empirically based on the best objective score acquired as per Section 3.1. Figure 4 illustrates the prediction process for one cluster centroid: when calculating the surprise score for generation t , the robots of generation $t-2$ are clustered into k trajectory centroids based on k -means; in generation $t-1$ the algorithm computes another set of k clusters. Finally, at generation t , k predictions are computed via linear interpolation from $t-2$ to $t-1$. The surprise score (Eq. (3)) is then calculated as the average distance from the four closest predicted trajectories, using Eq. (5) for d_s .

3.2.3 Novelty-Surprise Search: Novelty-surprise search (NSS) linearly combines the novelty and surprise scores as in Eq. (4). While the specific parameters of novelty search and surprise search remain unchanged (as reported above), the linear combination of novelty and surprise hinges on the λ parameter that controls the relative

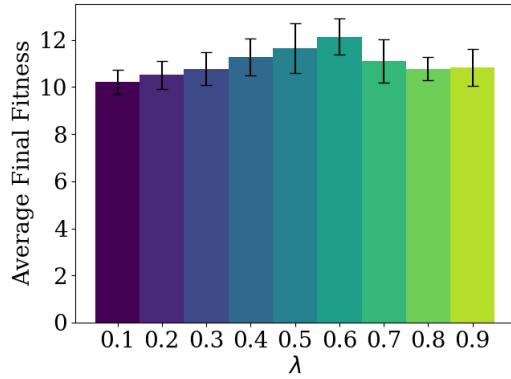


Figure 5: Sensitivity analysis of λ . The figure depicts the final average fitness of the fittest individuals obtained from 90 runs across nine λ values in the resolution $5 \times 5 \times 5$. Error bars display the 95% confidence interval of the average shown.

importance of the two rewards. In order to select the appropriate λ parameter, we run 9 experiments with λ ranging from 0.1 to 0.9. Each experiment is composed of 20 runs of the NSS algorithm with a particular λ parameter. Fig. 5 shows the average number of body length covered by the fittest individual across λ , for a representative resolution of $5 \times 5 \times 5$, chosen as it has already featured in previous work [2, 9]. We pick a λ that yields the highest average performance after 1000 generations: this happens for $\lambda = 0.6$, which leads to an average of 12.13 body lengths.

4 EXPERIMENTS

Previous work in the soft robot environment has explored the effectiveness of divergent search algorithms such as novelty and surprise search [9, 23]. As mentioned earlier, in this paper we instead focus on the performance comparison among four algorithms—namely novelty-surprise search, novelty search, surprise search and objective search—across eight different lattice sizes.

All reported results are obtained from 90 independent evolutionary runs. Significance is tested through two-tailed Mann-Whitney U -tests; significance is set to 5%. When performing multiple comparisons, the Bonferroni correction [3] is applied.

4.1 Experiment parameters

The simulation in VoxCad uses the same parameters as [23], in particular a gravity of -27.6 m/s^2 , a simulation time of 0.4 seconds, a rate of 40 Hz for the signal that actuates active voxels and a sampling rate of 100 Hz. Robots evolved in this paper have eight different lattice resolutions, from 3^3 to 10^3 . The evolutionary algorithm has a population of 30 individuals, which evolve for 1000 generations. Other CPPN-NEAT parameters are the same as in [2].

4.2 Efficiency

The main goal of robot locomotion is to evolve efficient behaviors, i.e. to have reached the most distant point at the end of the simulation. This section focuses exclusively on the 90 fittest individuals²

²The fittest individual of each independent evolutionary run is selected.

Table 1: Efficiency averaged from 90 independent runs (95% confidence interval in parentheses). Bold values are significantly different from all the other approaches.

| | OS | NS | SS | NSS |
|----------|--------------------|--------------------|--------------|---------------------|
| 3x3x3 | 7.74 (0.50) | 8.88 (0.19) | 9.32 (0.26) | 9.67 (0.23) |
| 4x4x4 | 8.13 (0.16) | 9.89 (0.35) | 10.71 (0.34) | 11.18 (0.36) |
| 5x5x5 | 7.51 (0.36) | 11.13 (0.33) | 10.73 (0.37) | 11.28 (0.30) |
| 6x6x6 | 8.38 (0.44) | 11.15 (0.28) | 11.43 (0.48) | 11.72 (0.30) |
| 7x7x7 | 8.07 (0.41) | 11.03 (0.37) | 10.57 (0.32) | 11.35 (0.32) |
| 8x8x8 | 9.23 (0.66) | 11.47 (0.39) | 11.35 (0.38) | 12.36 (0.41) |
| 9x9x9 | 8.32 (0.47) | 11.48 (0.37) | 11.08 (0.32) | 11.53 (0.38) |
| 10x10x10 | 9.29 (0.67) | 11.32 (0.38) | 11.18 (0.43) | 12.05 (0.35) |

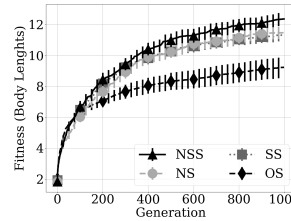


Figure 6: Efficiency averaged from 90 independent runs for resolution 8^3 across 1000 generations. Bars denote 95% confidence intervals.

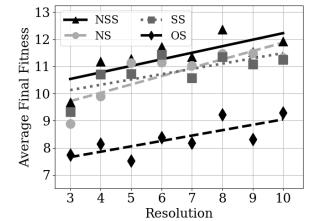


Figure 7: Relation between the resolution of the robots and the maximum fitness for resolution 8^3 across 1000 generations. Bars denote 95% confidence intervals of each approach (averaged from 90 runs).

(based on the characterization of Fig. 2a) collected from 90 independent runs across 8 resolutions. All values are normalized to the dimension of the 3D lattice (i.e. in body lengths of the robot).

Results from Table 1 show that NSS outperforms any other approach for every resolution selected: it significantly outperforms novelty search in 5 of the 8 resolutions tested (3^3 , 4^3 , 7^3 , 8^3 , and 10^3). As an example, Fig. 6 shows the efficiency of the four algorithms across 1000 generations for the resolution 8^3 : NSS outperforms novelty, surprise and objective search from generation 400 onwards.

Fig. 7 shows the results of efficiency across all the resolutions by means of linear regression. We can notice that every approach has a linear relationship between their final average efficiency and the robots' resolution, as their final average efficiency is highly correlated with lattice size ($r > 0.7$, $p < 0.05$ for each method except SS, where $r = 0.7$ and $p = 0.051$). As noted in Table 1 and observing the trends of the regression lines, we can notice that NSS constantly achieves better results compared to other approaches. The intercept values of NSS are significantly different based on an ANCOVA test ($p < 0.05$).

4.3 Robustness

Inspired by [7, 10], we investigate the *robustness* of each algorithm defined as the number of the fittest robots able to cover a certain threshold distance from their start point. While in other domains it is straightforward to define success (e.g. reaching the goal in a maze), robot evolution lacks a predefined goal. Under this perspective, we count the robots which cross several distance thresholds, and

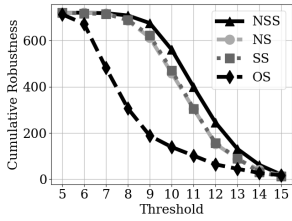


Figure 8: Number of successes, cumulated on all resolutions, for different performance thresholds.

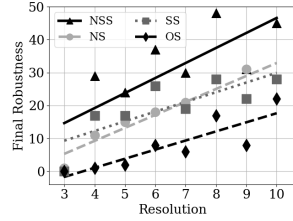


Figure 9: Relation between lattice resolution and the final robustness (threshold of 12 body lengths).

characterize them as “successful” if they are able to cover a distance greater than the selected threshold (in body lengths).

Fig. 8 shows the distribution of successes across different thresholds, cumulated across all lattice resolutions (i.e. 90 fittest robots for each of 8 resolutions). The distribution shows that generally NSS obtains more successes in thresholds between 8 and 14 compared to the other three algorithms. The robustness of novelty search and surprise search, on the other hand, is comparable across all shown thresholds. Unsurprisingly, objective search is outperformed by any other algorithm. It is important to note, however, that objective search is still able to evolve solutions even at higher thresholds and it eventually catches up to other approaches at threshold 14.

Fig. 9 shows the linear relation between the resolution of the lattices and the number of successes obtained with a threshold of 12 body lengths. This threshold was chosen because the four approaches show significant Pearson correlations between resolution and robustness ($r > 0.7$, $p < 0.05$ for each method); for all the other thresholds this condition does not hold. Observing the four regression lines of Fig. 9, NSS constantly achieves more successes compared to other approaches: the difference between the intercept values are significant according to an ANCOVA test ($p < 0.05$). As expected, novelty search and surprise search perform similarly with a very small advantage for surprise search at lower resolutions. Finally, objective search has fewer successes compared to divergent approaches, strengthening the evidence that the fitness landscape is deceptive across all resolutions tested.

4.4 Structural variety

To evaluate the variety of morphologies evolved by the four approaches, we investigate how each algorithm explores the structural space in two main feature dimensions, the number of filled materials and the number of bones (i.e. blue voxels).

In order to investigate how the different search processes explore the space of robot structures, we take inspiration from the feature mapping employed in the MAP-elites algorithm [24] to evolve soft robots. Unlike MAP-elites [24], structural diversity is not explicitly targeted in this case; it is interesting to see how this space is explored when the diversity criterion is behavior in terms of movement trails. To assess structural diversity, we compute the feature maps using the individuals evolved in one run sampled every 10 generations, and we add the individual in the map if the selected bin is empty or the fitness is lower compared to the individual tested.

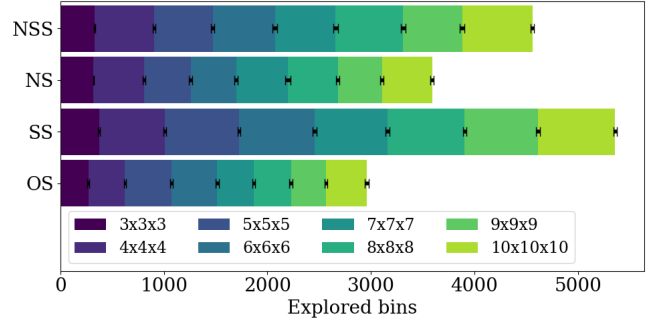


Figure 10: Average number of explored bins for all feature maps. Error bars display the 95% confidence interval of the average shown.

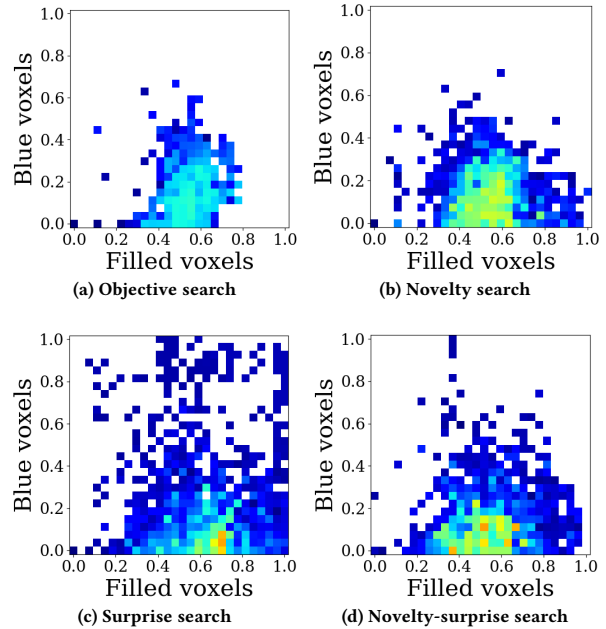


Figure 11: Sample feature maps produced by the four methods, for a single evolutionary run on a resolution of $8 \times 8 \times 8$. White bins do not have any robots, while colored bins denote the fitness of the best individual (blue for low fitness, red for high fitness).

In total, therefore, $3 \cdot 10^3$ individuals are tested per run; results are averaged from 90 independent runs per lattice resolution. The two feature dimensions are the same as in [24]: the percentage of the voxels filled (x -axis), and the percentage of blue stiff voxels, i.e. bones (y -axis). An example of the feature maps and the binning method is shown in Fig. 11. As the smallest lattice resolution is 27 voxels, the feature maps have a resolution of 27×27 .

Fig. 10 shows the number of explored bins averaged across 90 runs for each of the eight lattice resolutions. Interestingly, novelty search and objective search tend to explore fewer bins in the two feature dimensions considered, while NSS and especially surprise

search are able to explore more broadly. In terms of the structures favored by the different EC methods, novelty search tends to favor consistently more filled structures composed of more active materials; on the other hand, SS tends to explore less filled structures composed of more non-reactive materials, as can be noticed in the example of Fig. 11. As a linear combination of novelty and surprise, NSS structures lie between these two “extremes”. This algorithmic property seems to be beneficial for divergent search in terms of performance (based on Section 4.2). Indeed, NSS finds significantly more bins in the feature space chosen compared to novelty search in 7 out of 8 lattice resolutions (except 3^3). However, surprise search finds significantly more bins in the feature space chosen compared to NSS in all lattice resolutions. The example robots shown in Fig. 12 attest to the variety of forms which can be well-performing while structurally different. Further, the figure shows four frames of simulation per robot that illustrate the variance in the way the different evolved morphologies move away from their starting point.

5 DISCUSSION

The goal of this paper was to test the performance of a recently introduced divergent algorithm, novelty-surprise search, in the soft robot evolution domain. Compared to earlier applications of the NSS algorithm in maze navigation [8] the task of evolving robot morphologies is both more complex and requires a more complex characterization of the robot’s behavior. The algorithm was compared against three baselines: novelty, surprise and objective search. Through the in-depth analysis of the evolved robots’ efficiency, robustness and structural characteristics, there are several insights on how the search processes differ. Overall, NSS has shown improvements in performance both in terms of efficiency and robustness. In [8] the working hypothesis was that novelty search and surprise search give orthogonal rewards; their combination should benefit divergent search, which seems to be confirmed by the evidence shown in this work.

Looking at the other two divergent search algorithms, their performance is not particularly different: robots evolved via novelty search or surprise search perform similarly both in terms of efficiency and robustness. As already noticed in [9], however, surprise search tends to explore the morphological space more expansively—especially in terms of the volume of filled materials or passive materials. It seems that the combination of novelty and unexpectedness results in a deeper exploration of the search space, as a greedy search only for novel behavior might “hide” less novel but efficient behaviors. Combining novelty with surprise alleviates that, as surprise may backtrack to previously seen behaviors [8]. Results obtained by objective search clearly show that the problem is deceptive, as it fails to reach similar performances compared to all divergent approaches in any of the 8 lattice resolutions tested. Moreover, the robots evolved by objective search are structurally more similar to each other compared to those evolved via the different divergent search alternatives. It is worth mentioning that while the structural variety analysis has focused on the rate of non-active materials and filled voxels (as in [24]), other structural properties could be relevant, such as the rate of active materials or more sophisticated distance measures. Moreover, the results might also be influenced by the chosen behavior characterization. A deeper

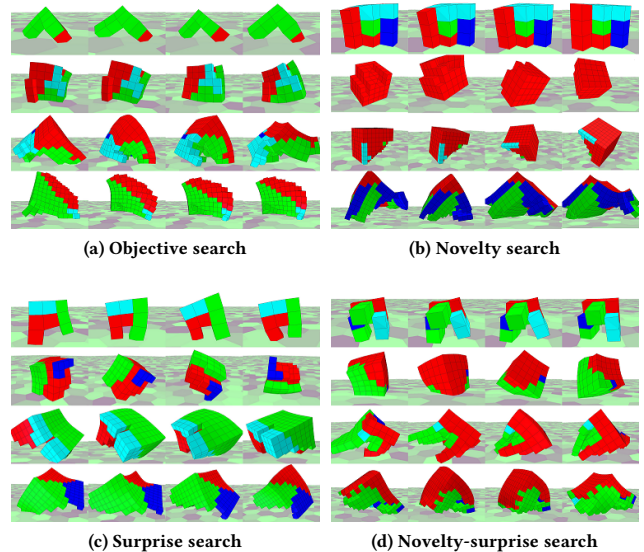


Figure 12: Fittest robots evolved in the first run of each approach for the resolutions $3 \times 3 \times 3$, $5 \times 5 \times 5$, $8 \times 8 \times 8$ and $10 \times 10 \times 10$ (from top to bottom). Four simulation frames are depicted for each robot.

analysis of the impact of different behavior characterizations on the diversity of evolved structures is planned in future work.

This is the first paper to methodically compare the performance of soft robot evolution across different lattice resolutions. Admittedly, the main motivation for this analysis is to test how sensitive each of the divergent search approaches is to the granularity allowed per morphology. Results show that NSS is consistently more efficient than the other algorithms when considering all 8 resolutions tested as a whole (via ANCOVA tests), showing that the algorithm can scale to more or less complex problems. Notably, larger lattices generally lead to more efficient behaviors, with robots of 27 voxels reaching 20% shorter distances (normalized to robots’ body lengths) than robots with 1000 voxels. This is perhaps not surprising, as a higher resolution allows for more expressive morphologies (more voxels to choose from) and more robust behaviors. While a direct representation would be challenged by the higher resolutions, the indirect encoding (via CPPNs) can scale and perform better at higher resolutions for all EC methods tested.

Experiments in this paper focus on diversifying the behavior of the evolved soft robots; to do this, we use several behavior characterizations (for the objective, for the distance, and for prediction in surprise search) which have featured extensively in previous work [2, 9]. Other behavior characterizations however have been proposed [23] and could be potentially used to measure distance, e.g. $d_n(i, j)$ in Eq. (1) and $d_s(i, j)$ in Eq. (3). Future work could explore how SS and NSS perform using such alternative behavioral characterizations both for distance and for prediction estimation. Another characterization could be used altogether: following [24], for instance, structural properties could be used to measure diversity. The high structural diversity exhibited by surprise search

and NSS in Section 4.4 could point to a potential use of these EC methods to explore the structural feature space itself, e.g. to bias search in MAP-elites[24]. More broadly, novelty-surprise search could be implemented as a quality-diversity algorithm for soft robot evolution, e.g. by including a local competition objective [19].

While future work should explore how NSS performs with alternative behavioral or algorithmic parameters (e.g. as a driver for quality-diversity and illumination algorithms), the VoxCad simulation for soft robots is extremely computationally heavy. This is especially true as resolutions increase: indicatively, for resolutions of $10 \times 10 \times 10$, one evolutionary run takes 88.2 CPU hours. To address this, another possible direction for future work could explore surrogate models [14] in combination with divergent algorithms. Using a surrogate model may make the discovery of efficient robots more difficult given the deceptiveness of this domain, but it would certainly boost the number of evaluations and experiments which could be performed. Therefore, a trade-off between efficiency and computational cost needs to be explored.

6 CONCLUSION

This paper explored how combining novelty and surprise affects soft robot evolution, both in terms of performance and in terms of variety of evolved structures. In particular, four approaches were compared: objective search, novelty search, surprise search and novelty-surprise search. Extensive experiments which vary the impact between novelty and surprise (λ) and vary the number of voxels available for the robot showed that the combined search for novel and surprising solutions can be advantageous. In terms of performance, evolved robots can reach further compared to other divergent approaches, considering all lattice resolutions tested. In terms of structural diversity, novelty-surprise search maintains a higher population diversity than novelty search with regards to two structural features. Based on our results, we foresee three main directions for future work: (a) exploring how structural diversity can affect evolution when used as objective or distance characterization; (b) testing how surprise (or novelty-surprise) can be integrated into quality-diversity algorithms such as novelty search with local competition [19] or MAP-elites [24]; (c) assessing the performance of divergent search and quality diversity algorithms in combination with surrogate modeling.

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