Towards open-ended evolution based on CVT-MAP-Elites with dynamic switching between feature spaces

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Introduction

Evolution is open-ended in the sense that it invents astronomical complexity for near-eternity (Brant and Stanley, 2017). ALife researchers consider open-endedness as a path to AI, which is distinctly different from today's approach to AI research, where optimization for specific objective performance is ubiquitous. Open-ended evolution (OEE) has been classified into four categories in the Tokyo category (Packard et al., 2019) after the York category (Taylor et al., 2016), and more recently into three categories: Type 0: Variation, Type 1: Innovation, Type 2: Transformation (Stepney, 2021). Quality-Diversity and coevolution have been investigated as main keys to open-endedness, and algorithms applicable to various problems have been proposed including Novelty search (Lehman and Stanley, 2011), MAP-Elites (Mouret and Clune, 2015), Minimal criterion coevolution (MCC) (Brant and Stanley, 2017), Generative adversarial networks (GANs) (Goodfellow et al., 2014), and Paired open-ended trailblazer (POET) (Wang et al., 2019). This study follows the former line of research (diversity) while aiming to incorporate the idea of the latter line of research (coevolution). The purpose is to examine the hypothesis that repetition of dynamic switching of target features that escape selection pressure and increase diversity plays a significant role in open-ended evolution that leads to innovation (e.g., the evolution of flight). This evolutionary scenario could be interpreted as the result of dynamics similar to the coupling of guiding and hiding effects (Mayley, 1997), but working across feature spaces and even without learning, by a Quality-Diversity algorithm.

Specifically, we create an extended MAP-Elites algorithm that continuously produces interesting individuals by repeatedly switching feature spaces using some criteria in the process of exploring the feature space extracted from the possible phenotype space, and that achieves evolution that meets the criterion of Types 1 and possibly 2 (Stepney, 2021). We chose as the target of open-endedness a model of the emergence of communication in 3D virtual creatures based on the evolution of morphology and behavior. It has a significant gap between genotype and phenotype, of the type created by

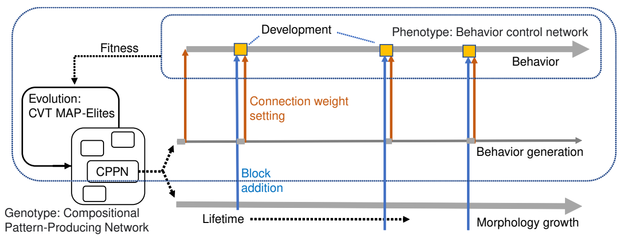

Figure 1. Overview of the model. The CPPN (genotype) controls ontogenetic development. The morphology and behavior of the creatures grow intermittently during lifetime. After the lifetime is over, the next generation population is generated by genetic operations.

evolved developmental plasticity due to the dynamic repetition of development during the lifetime of a creature. This would satisfy the fourth necessary condition of OEE (Soros and Stanley, 2014) that "the potential size and complexity of the individuals' phenotypes should be (in principle) unbounded".

This paper focuses on the evolutionary process that switches between 2D feature spaces based on specified criteria as a first step in our research. It would be improved by using the diversity created in the feature space to create new solutions either by mutation (goal switching) from a solution in a distant cell (bin) or by the intersection of solutions in two distant cells. We expect innovation to occur through goal switching beyond the feature spaces by going through the search in other feature spaces in addition to goal switching within the feature space. Although the dynamic generation method of feature spaces (Cully, 2019) aiming at convergence to the optimal solution is also attractive as a quick search method, we adopt switching between predefined feature spaces in the preliminary experiment for the purpose of basic research on the above hypothesis.

Methods

Overview

We used a model (Komori et al., 2023) that extended EvoCreature (Seki et al., 2020). In the model, the 3D virtual creatures performed a given task by moving around the flat field where a sound source was placed during T steps.

Figure 1 shows the overview of the model. Each creature had its CPPN (Compositional pattern producing networks) (Stanley, 2007) as its genotype. Starting from a single rectangular block, the morphologies of the creatures developed into multiple blocks, connected by hinges, through ontogenetic development based on the CPPN output. New blocks were added anywhere on the body surface. The behavior of each creature was generated by changes in the angle of the hinges between the blocks based on the output of the behavior control network (BCN), a three-layer neural network generated by the CPPN. The structure and weights of BCN were updated by CPPN output at each ontogenetic development. The creatures received sounds from the sound source using sensors. They received information on the direction of the sound source, the amplitude and the frequency band of the sounds, which were inputs to the BCN. The amplitude attenuated with distance from the sound source.

Extended CVT-MAP-Elites

We propose an extended version of CVT-MAP-Elites (Vassiliades et al., 2017) as an evolutionary algorithm. CVT-MAP-Elites is a variant of MAP-Elites that supports higher dimensionality of a feature space by the centroidal Voronoi tessellation of a feature space. The extended version of CVT-MAP-Elites dynamically switches the feature space to search on the basis of two indices: the average fitness of elite individuals mapped in the feature space and the coverage ratio of the feature space, i.e., the ratio of the number of filled cells to the number of partitions in the feature space. If the two indices do not increase during the 10 generations, the feature space is switched from the current one to another in which different phenotype values create its space.

When switching the feature space, elite individuals mapped to the original feature space are mapped to the corresponding cells in the new feature space. If multiple individuals correspond to the same cell in the new feature space, only the one with the highest fitness is mapped.

Preliminary Experiment

We used a task in which 30 individuals, placed on a circle of radius 15 and facing the center, approached a sound source placed in the center of the circle. The fitness increased with the nearness of the distance between the final individual position and the sound source position, and took values between 0 and 1. The axes of the first feature space (S_A) searched were the number of body parts and the total amplitude of the received sounds. The axes of the next feature space (S_B) were the number of body parts and the individual volume. Finally, S_A was searched again. The experiment was terminated when the feature space switching criteria were satisfied during the second search for S_A.

Figure 2 shows the max and average fitness of elite individuals, the searched feature spaces before switching happened, and the two extracted individuals. The average fitness of elite individuals at the end of the second search for S_A was 0.11 higher than the average fitness of elite individuals at the end of the first search for S_A. This may indicate that switching between the spaces contributed to the adaptive evolution of complex creatures.

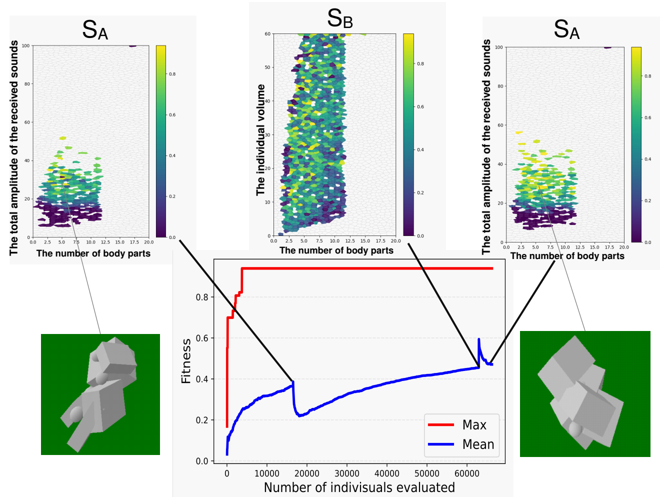

Figure 2. Results. The color bars represent fitness.

The results of Welch's t-test showed that the volume of individuals generated by the second search for S_A ($M = 4.46, SD = 4.36$) was larger than the volume of individuals generated by the first search of S_A ($M = 4.77, SD = 4.66$) ($t(20458) = -3.72, p < .01$). Since individuals with diverse volumes are retained while searching S_B, in other words, the volume of individuals was hidden, the population may have been able to escape from a local optimum that they had been stuck in during the first search for S_A.

Furthermore, we focused on the two individuals in the same cell with the largest difference in fitness of elite individuals obtained in the first search for S_A and in the second search for S_A shown in Figure 2. Compared to the individual obtained in the first search, the individual obtained in the second search had the same number of body parts, but was 9.04 larger in volume and moved more slowly. The slowness of the movement may have led to staying at the target site at the end of the lifetime, leading to its higher fitness.

Conclusion

We extended CVT-MAP-Elites to evolve the control and body structure of 3D virtual creatures by switching the search of the 2D feature space based on specified criteria. The results showed that switching the search of the feature space changed the body structure of the generated creatures and their associated movement patterns. We are currently experimenting with continually alternating S_A and S_B searches.

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