# How excessive elitism can facilitate the evolution of morphology and behavior of artificial creatures with NEAT

Siti Aisyah Binti Jaafar†, Reiji Suzuki, Satoru Komori and Takaya Arita

Graduate School of Informatics, Nagoya University
†E-mail: binti.jaafar.siti.aisyah.v4@s.mail.nagoya-u.ac.jp

## Introduction

An approach to evolve artificial creatures is getting much interest both in scientific research (e.g., evo-devo (Gupta et al., 2021; Shah et al., 2021)) and engineering research (e.g., design of soft robots (Schmitt et al., 2018; Wehner et al., 2016; Chiba et al., 2020).

However, when they incorporate various factors regarding the above topics into the model, the increase in the evaluation cost for the physical simulation is not negligible. The reduction of evaluation cost in evolutionary computation has been extensively discussed (Giráldez et al., 2005; Stoy, 2022), and small population size is often used as an ad hoc way to resolve the problem, while it can cause premature convergence of the population to local optima.

Many studies have implemented elitism in evolutionary algorithms (la Cava & Moore, 2018; Methenitis et al., 2015). With this method, the best individuals from one generation are carried over to the next generation unchanged, which can improve the performance of the algorithm. However, the role of elitism in reducing the evaluation cost of artificial creatures in the population has not been discussed.

This paper summarizes an approach proposing a simple method based on a novel use of elitism to increase the population size of artificial creatures while keeping the evaluation cost small, which can contribute to preventing the population from premature convergence (Jaafar et al., 2023). We propose the "Excessive Elitism (EE)" method by modifying elitism in HyperNEAT (Hypercube-based NeuroEvolution of Augmenting Topologies) (Stanley et al., 2009), which is an evolutionary algorithm frequently used to evolve genotype (i.e., Compositional Pattern Producing Network (CPPN) (Stanley, 2007)) of artificial creatures. In the excessive elitism, the evaluated fitness of best-fit individuals will be succeeded and reused instead of being re-evaluated during subsequent fitness evaluation. This method can reduce the evaluation cost if the elite size is in excess.

## Evolutionary Model

In this study, we used an evolutionary framework of artificial creatures in a 3D-multi-agent environment based on Python module-based physics engine, PyBullet, to discuss eco-evo-devo in evolving artificial creatures (Fig. 1), described in (Jaafar et al., 2023). Each rigid-bodied creature consists of rectangular blocks connected with hinges. Their morphology develops by adding new blocks to the existing body blocks in several fixed time steps in their lifetime. A genotype of a creature generates two neural networks, one determines (a) the morphological development (i.e., the addition of a new block or not, the length of the long sides of the new block, hinge direction, and to have fixed hinge or flexible joint) and the other determines (b) the behavioral generation process (i.e., hinge angles) according to the sensory inputs (e.g., the distance between coordinate of the creature and target, the orientation of creature towards the target, and the elapsed time from the beginning of fitness evaluation) obtained by a radar sensor.

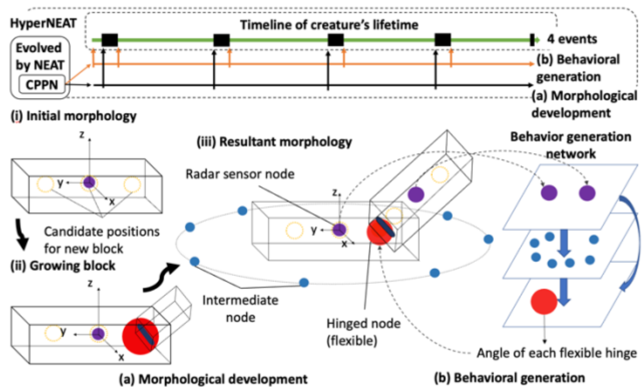


Fig. 1: Overview of the artificial creature framework.

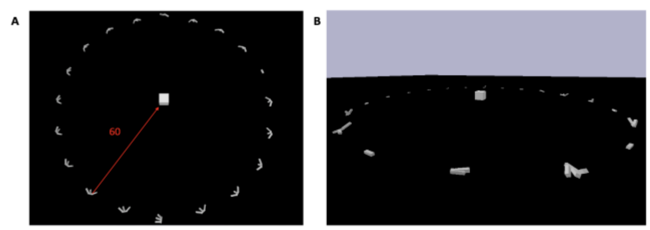


Fig. 2: Environment and Task.

Fig. 2 shows a field for fitness evaluation. Using a locomotion task, we conducted experiments to see how excessive elitism can affect evolution. Artificial creatures were arranged in a circular manner, surrounding a target (cube) in the center on a flat surface. Fitness was defined as the distance traveled by creatures from the initial position to the target.

The Hyper-NEAT is an evolutionary algorithm for evolving complex neural networks represented by the Compositional Pattern-Producing Network (CPPN) (Stanley, 2007). We adopt this to evolve the CPPNs used in the morphological development and behavioral generation as the genotype of each artificial creature (Fig. 1 (a), (b)). We assume that a single large CPPN determined by the genotype of a creature represents both CPPNs as its sub-networks.

## Excessive Elitism Method

We modify the elitism in NEAT, commonly defined as the procedure that the best-fit *M* individuals in each species will be preserved as-is from one generation to the next. In excessive elitism, the best-fit *M* individuals will become elite regardless of their species in the whole population of *N*, assuming an excessively large *M*. Their genotypes will be passed on to the next generation. We also assume that their evaluated fitness will be succeeded and used as their fitness value instead of re-evaluating it in the subsequent generations. The other non-elite individuals (*N*-*M*) generated by selection and genetic operations are the only ones that need to be evaluated at each generation. Therefore, this significantly reduces the evaluation costs for each generation if the elite size (*M*) is excessively large. We expect that high diversity kept in the large population would prevent the population from getting stuck in local optima, while the speed of evolution may slow down due to the small number of evolving individuals (*N*-*M*).

Precisely, in this study, all *N* individuals were placed into the field, but only non-elite (*N-M)* individuals (in the previous generation) moved through their lifetime for evaluation, while the other elite individuals (*M*) were stagnant to reduce the cost. All individuals were evaluated in the first generation.

## Experiments and Results

Fig. 3 (a) shows the experimental setup for two cases of *N* and *M*. First, we assumed a baseline case (BC) in which a small population size (*N*=20) was used due to the strong limitation of the evaluation cost (*N*-*M*=18) and adopted a standard small elite size (*M*=2). Then we focused on how excessive elitism (*M*=82) increased population size (*N*=100) without increasing evaluation cost (measured by the time (sec) / generation) and contributed to the adaptive evolution of creatures (EE). Finally, we carried out ten trials for each case for 400 generations and adjusted them according to the evaluation cost to compare the performances equivalently.

The average of the best fitness in BC increased and converged to around 20 (BC-i), which means that the baseline case often caused premature convergence of the population to suboptimal individuals who could not reach the target (BC-iii). On the contrary, the best fitness in EE reached almost the maximum value of 50 (EE-i), showing that the population could evolve to reach the target in most trials (EE-iii), while the evaluation cost was comparable (160 sec/gen) with that in BC (120 sec/gen). The slight increase in the evaluation cost for EE approach might be due to the computational cost for simulating the whole physical field regardless of the number of evaluating individuals.

We expect this difference between the cases is due to a stronger evolutionary tendency that individuals with a larger number of blocks (e.g., 20) tended to be adaptive and dominate initially in BC (BC-ii). However, these individuals were too complicated to evolve further to obtain better morphological structures (Fig. 3 (b) BC). On the contrary, the excessive elitism

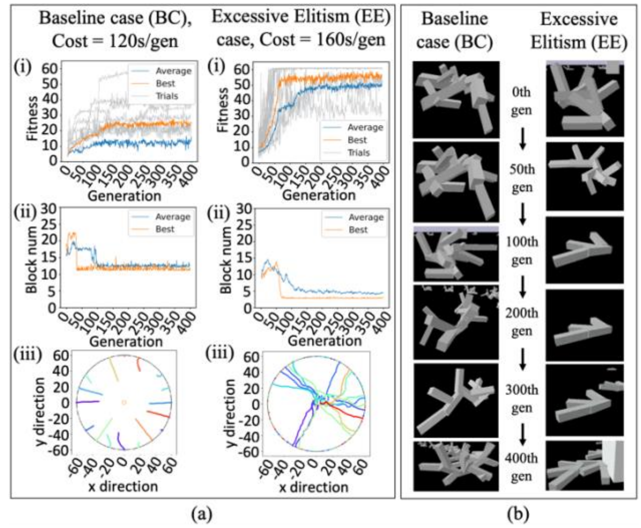


Fig. 3: (a) (i) the evolution of the fitness (average and best) among 10 trials, (ii) the number of blocks (average and best), and (iii) the trajectory of individuals in the last generation of the best trial. (b) The snapshots of the best creatures in the best trial from the first to the last generation. Left: Baseline case (BC), right: Excessive elitism case (EE).

kept diversity in the population, which allowed the individuals with the smaller number of blocks (e.g., 4) to survive and evolve to be simple and adaptive (Fig. 3 (b) EE).

In addition, we conducted experiments with excessive elitism in a small population (*N*=20, *M*=18), where the average fitness improved slightly (around 35-40) compared to the baseline case. While the evolution of a large population without excessive elitism (*N*=100, *M*=2) often resulted in poor average fitness (around 20-25) at a five times larger evaluation cost, where the field was congested with individuals who had a larger number of blocks.

## Conclusion

We proposed the excessive elitism method that would improve the evolution of artificial creatures by increasing the population diversity, which enables the population to avoid premature convergence at a small evaluation cost. Nonetheless, it is worth noting that certain non-adaptive individuals with initial conditions may accidentally achieve high fitness (Montanier et al., 2011; Jin et al., 2005). Despite this challenge, the benefits of EE method are significantly greater, effectively outweighing the problem. Additionally, EE shares associations with quality-diversity approaches like MAP-Elites, which captures diverse high-performing solutions by partitioning the search space. In this study, EE method demonstrates the simplest means of securing a niche and maintaining diversity within the general framework of a simple genetic algorithm. Further investigation is yet to be done to realize the potential of EE method in a different and more complex environments.


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