Hochschule Düsseldorf
University of Applied Sciences

Fachbereich Elektro- und Informationstechnik
Faculty of Electrical Engineering and Information Technology

Künstliche Intelligenz: Agenten, Expertensysteme und evolutionäre Algorithmen

Thema:

Genetic Algorithm with Speciation (Artbildung)

Hamid Fallah
Martikelnummer: 956248

Herr Gregor Braun
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1. Introduction

A Genetic Algorithm (GA) is an optimization method inspired by the process of natural selection. It belongs to the family of evolutionary algorithms and is used to find approximate solutions to complex optimization and search problems. GAs work by evolving a population of candidate solutions through the principles of selection, crossover, and mutation. The most promising individuals are selected to produce offspring for the next generation, gradually guiding the population toward better solutions.

2. How a Genetic Algorithm Works

A typical GA follows these steps:

Initialization: Generate an initial population of individuals (candidate solutions), usually at random.
2. Evaluation: Each individual is evaluated using a fitness function to determine how good the solution is.
3. Selection: Select individuals based on fitness to act as parents.
4. Crossover: Combine two parents to create one or more offspring, mixing their traits.
5. Mutation: Apply small random changes to offspring to maintain diversity.
6. Replacement: Replace the old population with the new one (or a mix of old and new).
7. Termination: Repeat steps 2–6 until a stopping condition is met (e.g., maximum generations or convergence).

3. Project Description

This project focuses on using a genetic algorithm to optimize a multimodal function, which has two distinct peaks (optima) located at different positions along the x-axis. The objective is to:

- Implement a genetic algorithm to explore this fitness landscape.
- Introduce the biological concept of speciation: splitting the population into subgroups (species) that no longer interbreed.
- Evaluate whether speciation helps in identifying multiple optimal solutions (one species per peak).

4. Implementation

The implementation follows the core structure of a genetic algorithm with an added speciation mechanism. The steps are:

4.1. Initialization:

- A population of 100 individuals is created.
- Each individual represents a scalar value x in 1D space, initialized randomly in the range [-5, 5].

4.2. Fitness Function:

- The fitness landscape is a fitness(x)=exp(−(x+2)^2)+exp(−(x−2)^2) with two peaks centered at x = -2 and x = +2.
- Individuals closer to either peak have higher fitness.

4.3. GA Evolution:

- The algorithm evolves the population using:
- Selection: Prefer individuals with higher fitness.
- Crossover: Mix two parents to create an offspring.
- Mutation: Slightly perturb offspring for diversity.
- This phase is run for a number of generations (e.g., 10 or 30) before speciation.
- During this time, the population explores the landscape, potentially beginning to converge around one or both peaks.

4.4. Speciation (at a defined generation):

- At a certain generation (e.g., 10 or 30), the population is split into two species based on Euclidean distance.
- This is done by identifying the two individuals that are furthest apart, and grouping the rest based on proximity to those.
- The result is two genetically isolated species.

4.5. Independent Evolution After Speciation (Generations speciation from 10 or 30 to 59):

- Each species evolves separately:
- They perform their own selection, crossover, and mutation operations.
- There is no interbreeding between species.
- This mimics biological speciation: once species are formed, they evolve in parallel paths.
- The experiment runs for a total of 60 generations.

4.6. Tracking:

- All individuals' positions and species are recorded over time.
- Results are visualized to show where each species converges.

5. Results of Initial Experiment (Speciation at Generation 10)

In the first experiment, speciation occurred early — after only 10 generations.

5.1. Before speciation:

- The population was still diverse and spread across the domain.
- Individuals were exploring both the left and right peaks.

5.2. After speciation:

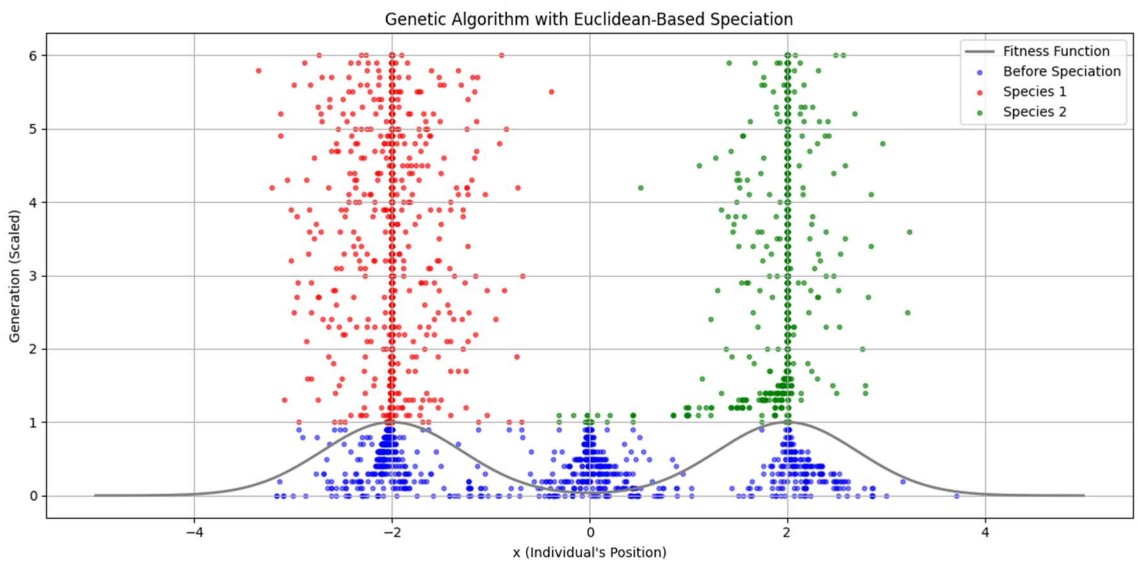
- The population was split into Species 1 (red) and Species 2 (green) using Euclidean distance.

- Species 1 converged to the left peak at x ≈ -2.
- Species 2 converged to the right peak at x ≈ +2.

The populations evolved in isolation and effectively covered both optima.

5.3. Key Insights:

- Early speciation allowed both peaks to be explored and optimized.
- Species separation prevented premature convergence to a single solution.
- This result aligns perfectly with the project's hypothesis that speciation helps in multimodal optimization.



6. Modification: Delaying Speciation to Generation 30

To test the impact of late speciation, the experiment was repeated with speciation delayed to generation 30.

6.1. Before speciation:

- The population was evolved for 30 generations as a unified group.
- Over time, the population converged almost entirely to the left peak.
- Diversity was significantly reduced, with very few individuals exploring the right side.

6.2. At generation 30:

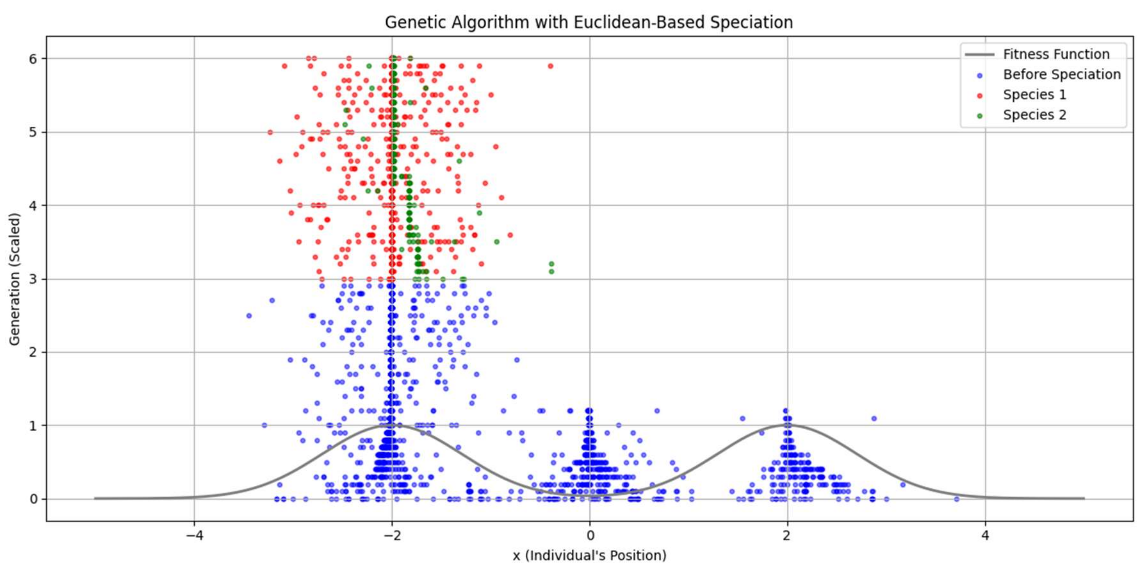
- Speciation was applied, but the population was already highly clustered.
- Species 1 contained 94 individuals around x ≈ -2.
- Species 2 had only 6 individuals with lower diversity and further from any optimum.

6.3. After speciation:

- Both species remained in the left peak.
- The right peak was not explored at all.
- Species 2 did not have the diversity or size to recover or explore new areas.

6.4. Key Insights:

- Delaying speciation until the population had already converged rendered it ineffective.
- The resulting species were unbalanced, and optimization focused solely on one peak.
- This confirms that speciation must occur before convergence to preserve diversity.



7. Analysis and Comparison

Criterion	Early Speciation (Gen 10)	Late Speciation (Gen 30)
Diversity before split	High	Low
Population split	Balanced	Heavily skewed
Right peak reached?	Yes	No
Optimization coverage	Both peaks	Mostly left peak only
Effectiveness	High	Low

The comparison clearly illustrates that early speciation is crucial for multimodal optimization. Waiting too long leads to premature convergence and loss of useful diversity.

8. Conclusion

This project successfully demonstrated the importance of speciation in genetic algorithms, particularly in the context of multimodal optimization. The timing of speciation has a significant impact on the algorithm's ability to find and maintain multiple optima.

9. Summary

By simulating natural speciation, we exprimented the GA's ability to handle complex landscapes with multiple optima. Speciation at the right time effectively preserved diversity and enabled the population to split and explore distinct solutions. The experiment confirmed that premature convergence is a real risk when speciation is delayed, reinforcing the importance of early intervention in evolutionary strategies.