A Comparison of Objective-based Search, Novelty Search, Combination Search, and Resource Search on the Maze Problem

Braden McDorman[1] and Dean Hougen[2]
School of Computer Science
University of Oklahoma, Norman, OK 73072
[1] bmcdorman@ou.edu
[2] hougen@ou.edu

Abstract

Popular methods of evolutionary computation (EC), such as objective-based search and novelty search, have previously been analyzed on the Maze Problem. While novelty search has been shown to outperform objective-based search on the Maze Problem, novelty search fails to take advantage of the fitness landscape at all to guide the evolutionary process. We propose two new evolutionary algorithms (EAs) for addressing the seeming dichotomy between these two methods: combination search – a weighted combination of objective-based and novelty heuristics – and resource competition. We analyze these four methods on 205 static mazes of varying complexity for both success rate and number of agents evaluated. Our results show that resource competition outperforms objective-based search by as much as 123% and novelty search by as much as 65%, while also reducing number of agents evaluated. Results also indicate that combination search does not perform significantly better than novelty search. We conclude that resource competition is a better EA for solving the Maze Problem and potentially other problems where objective-based and novelty search is used.

1 Introduction

Objective-based search uses a fitness heuristic to reward agents that approach the desired optimum of the problem space. Fitness heuristics, however, suffer from the problem of deception. The problem of deception is the notion that to reach the desired optimum of the problem space, evolutionary steps must be taken that do not directly align with the fitness heuristic. Novelty search, a recent alternative to objective-based search, abandons the concept of objective fitness in favor of rewarding agents purely for their phenotypic or genotypic "novelty".

One of the first problems used to show the efficacy of novelty search was the Maze Problem. In this genetic programming problem, agents must evolve a solution from the beginning point of a static maze to the desired end point. Mazes are inherently deceptive problem spaces, making them good candidates for alternatives to purely objective-based EAs. It is simple to intuitively understand why this is the case. If agents gain objective fitness for their euclidean distance from the desired end-point, this means that it is possible that the corner of a room – an evolutionary dead-end – will be rewarded as more fit, while an agent that begins to evolve towards a room's exit will be penalized as less fit. Since there is no incentive for an agent to evolve towards an exit, objective-based search may get stuck and fail to solve the maze problem.

Novelty search has been previously shown to outperform objective-based search in solving the Maze Problem. [**?**] Once again, it is simple to gain an intuitive understanding of why this is the case. Agents that reach previously undiscovered parts of the maze will be rewarded as more likely to reproduce. Eventually the desired end-point will be discovered as an ever increasing amount of the problem space is searched. Though this be the case, there is still a relationship between the objective fitness heuristic of the problem space and the maze solution. By abandoning the fitness landscape entirely, novelty search cannot exploit this relationship at all.

We propose two new EA methods for combining the seemingly dichotomous nature of objective-based search and novelty search. The first method, combination search, combines a weighted average of both objective-based fitness and the novelty metric to assign an overall fitness to an agent. The second method, resource competition (herein referred to as resource search), forces phenotypically or genotypically similar agents to compete for a limited amount of food non-uniformly distributed throughout the search space.

2 Hypotheses

The first goal of this study is to verify previous experiments performed with novelty search on the maze problem. After verification of previous results, the next goal is to extend the experiment to evaluate the two proposed EAs for solving the maze problem: combination search and resource search.

We formed three different hypotheses to achieve the goals of this study:

H_1 As previously shown by Lehman et al, we expect novelty search to outperform objective-based search. [**?**] Verification of this hypothesis validates this study's experimental method, permitting comparison to the two proposed EA methods.

H_2 We expect combination search, a weighted combination of objective-based search and novelty search, to outperform both of its constituents. We predicted that this EA method would receive the benefits of both novelty and fitness-based metrics, creating a guided search capable of overcoming deception in the search space.

H_3 We expect resource search to outperform both objective-based search and novelty search. Like combination search, we predicted that resource search would result in a guided search while also overcoming deception.

3 Method

To test these hypotheses, we replicated an earlier experiment by Lehman et al in which a robot controlled by a genetic program must navigate a maze from a starting point to an end point within a fixed number of movements. [**?**]

Mazes are inherently deceptive problem spaces. Simple euclidean distance between the agent and goal, for example, may not paint an accurate picture of the agent's success at solving the problem. As such, mazes are excellent candidates for replicating the conditions of more complex ECs.

Mazes were divided into five difficulties: simple, moderate, hard, harder, and hardest. Difficulty was determined by maze wall density, goal path length, and maze dimensions. 41 mazes for each difficulty were generated. Each method was then evaluated on every generated maze three times – once with a generation cap of 200, once with 400, and once with 600.

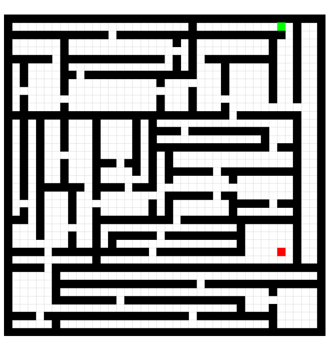

Figure 1: A sample maze from the "hardest" set. Green is the starting point. Red is the end point.

Five EA techniques were compared in our research: random search, objective-based search, novelty search, a combination of objective-based and novelty search, and resource search. Total agent evaluations and the percent of mazes solved were recorded for every method.

All five compared methods feature different strategies for agent selection during reproduction. Once selection has been performed, however, the parameters for reproduction and mutation are identical. A simple tree cross-over is performed for reproduction. The children are then mutated against a randomly generated tree through node cross-over. All reproduction is performed with replacement.

In random search, agents are randomly crossed over and mutated with no regard for the agent's fitness heuristic or novelty metric. This provides an experimental control as a baseline for comparison.

In objective-based search, agent fitness is calculated to be the euclidean distance from the agent's ending point to the desired end point.

In novelty search, the novelty factor is calculated to be one minus the normalized average euclidean distance from the agent's ending point to all agent ending points from previous generations.

Combination search computes both objective-based fitness and novelty factor and returns the midpoint of the normalized values.

Resource search places units of "food", a positive integer, at every cell in the maze. The amount of food available at a given cell is proportional to its euclidean distance from the desired end-point. As such, food units monotonically increase towards the desired end-point. Upon completing evaluation, agents "eat" two units of food from their end-point and one unit of food from all adjacent cells. If the requisite amount of food is available, the cell's food count is decreased by the amount eaten. If the requisite amount of food is unavailable, the agent "dies" and is removed from the viable mating pool for the next generation. To create selection pressure, the target population size of the next generation is double the size of the viable mating pool. Agents are randomly crossed-over and mutated until the target population size is reached.

4 Results

As shown in figure 2, novelty search outperforms objective-based search, random-search, and combination search in solving the maze problem. Figure 3 shows that novelty search requires 12 percent fewer agent evaluations than objective-based search and it solves 56 percent of mazes with 600 generations while objective-based search only solves 41 percent with 600 generations.

Resource search significantly outperforms novelty search, objective-based search, a combination thereof, and random search in successfully solving the maze

Terminals:	**move**: Move forward one square if possible. **left**: Turn 90 degrees left. **right**: Turn 90 degrees right
Nonterminals:	**if_wall_ahead**: Execute the left child if a wall is directly ahead, right otherwise. **if_goal_ahead**: Execute the left child if the goal lies within a 90 degree cone projected outwards from the robot, right otherwise. **prog2**: Sequentially execute the left and right children
Fitness cases:	One of 205 randomly-generated mazes (divided into 5 difficulties).
Wrapper:	Program repeatedly executed for 300 terminal actions.
Population size:	500 (variable for resource search)
Termination:	Maximum generations = {200, 400, 600}.

Table 1: Maze problem parameters

Difficulty	**Random**	**Objective**	**Novelty**	**Combination**	**Resource**
Simple	38	41	41	41	41
Moderate	34	38	41	40	41
Hard	16	27	36	36	41
Harder	10	16	32	29	41
Hardest	8	17	23	23	38

Table 2: Successful completions with a generation cap of 600

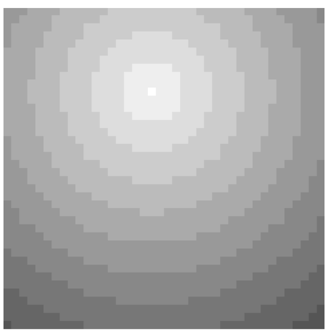

Figure 2: Food is placed proportionally to the euclidean distance from the goal. This distance is scaled by a scaling factor to create food units.

problem in all tested difficulties and maximum number of generations. This result is most pronounced in the "hardest" difficulty of mazes, as seen in figure 2. Figure 3 shows that resource search also requires a minimal number of agent evaluations to achieve its high success rate when compared to the other methods presented in this study. When compared to objective-based search, for example, resource search requires 40 percent fewer evaluations and successfully solves 123 percent more mazes. When compared to novelty search, resource search requires 31 percent fewer evaluations and successfully solves 65 percent more mazes.

Combination search did not outperform novelty search as expected. Instead, results indicate that it performed either as well or slightly below novelty search in success rate.

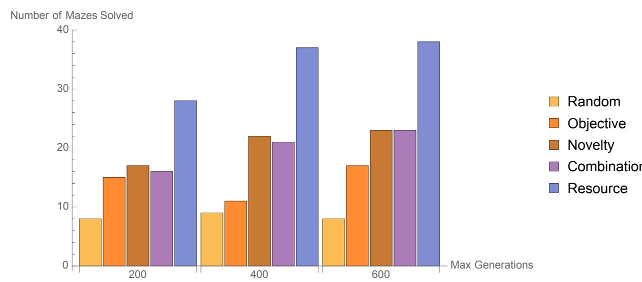

Figure 3: Number of successes on the "hardest" difficulty of mazes.

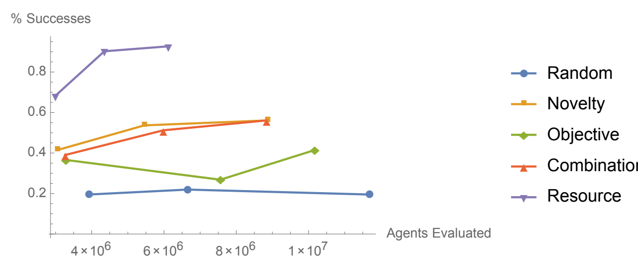

Figure 4: Agents evaluated vs percent successes for 200, 400, and 600 generations on the "hardest" difficulty of mazes.

5 Discussion

In this study we demonstrated the efficacy of resource search when applied to the maze problem and reaffirmed the results of previous experiments with novelty search. We also showed that a combination of novelty and objective-based search does not significantly outperform its constituents on the maze problem. We hypothesize the advantages of resource search are due to its ability to harness objective-based fitness through resource distribution while not penalizing novel agents that may overcome deception in the problem space.

This study failed to prove combination search performs better than its constituents. It is possible that instead of inheriting both novelty search and objective-based search's advantages, it inherited both of their disadvantages.

Resource search requires a scaling factor to determine how many units of food are placed at a given cell with regard to its euclidean distance from the desired endpoint. Since units of food are integer values, this results in plateaus of equal fitness, or levels. This parameter may be modified to control the selection pressure.

While resource search is comparable to fitness sharing approaches at face-value, there are several important differences that make resource search unique. Fitness sharing algorithms reduce the fitness of agents in densely-populated areas of the problem space. The intent of fitness sharing is to encourage novelty by rewarding such behavior. This method, though, still relies on an objective-based fitness function. As such, fitness sharing does not alleviate the underlying problem of deception with objective-based fitness functions. Resource search does not suffer from this fundamental issue.

We believe that resource search's relationship to biological evolution may be, in part, responsible for its high performance.

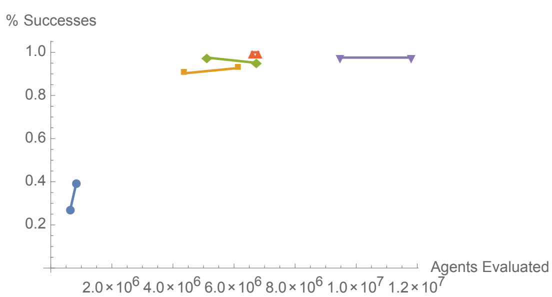

Figure 5: A comparison of resource search with a varying number of resource levels (400 and 600 generations)

While resource search uses a variable population size, the average number of agent evaluations required to find a solution is lower than the other, fixed population size, EAs. As seen in figure 4, resource population grows over time as agents discover phenotypes with abundant resources.

Resource search as implemented in this study requires a priori information of the search space. The maze problem features a discrete number of demonstrable phenotypes (grid cells) that allow discrete placement of resources for resource search. Furthermore, food distribution must be scaled by an arbitrary scaling factor. It should be noted that performant implementations of novelty search using k-nearest neighbors to determine sparseness also requires a priori knowledge of the search space. [?]

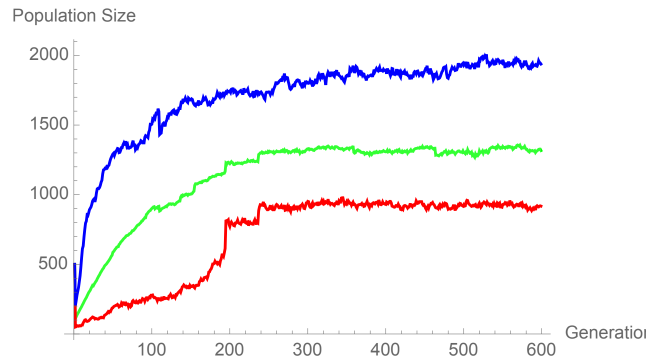

Figure 6: Population size grows over time as agents discover more resources closer to the goal. Blue is the maximum observed population size, green is the average observed population size, and red is minimum observed population size.

6 Future Work

As previously mentioned, resource search uses an a priori scaling factor to place food at discrete phenotypes. We believe, however, that resource search can be extended to problems that feature an non-discrete of phenotypes.

Resource search might be further improved by synthetic sympatric speciation to encourage niching behaviors. After culling the population into a viable mating pool, resource search indiscriminately reproduces agents. We wish to introduce a "choosiness" parameter into the agent's chromosome that controls the phenotypic or genotypic mating range of that agent. This parameter may serve to maintain niches and further improve performance of resource search.

We believe that resource search preserves a diverse population better than objective-based or novelty search. As such, if the population is introduced into a new environment, we expect resource search to outperform these methods. Experimentally verifying this hypothesis would be an important step in developing a more complete picture of the algorithm.

While combination search failed to out-perform its constituents in solving the maze problem, applying different weights to each factor may lead to performance improvements. This paper only evaluated combination search at a 0.5 weighting for each factor.

While this paper postulated performance advantages over fitness sharing, this has not been experimentally verified. Verifying this claim is an important next step for resource search.

This study's experimental source code and data is freely available for independent verification of its results and future work. [?]

7 Acknowledgements

To be inserted.