A Literature Review of Maze Generation Guided by Difficulty Scoring

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that can be used to describe a maze's solution in order to generate mazes that fit closely with the user's specifications [4].

1 INTRODUCTION

Mazes are simple but effective domains for testing search algorithms. Within computer science, easily understood domains are frequently used to analyze the effectiveness of algorithms. These domains tend to be easy for both the computer and the researcher to understand. Mazes, as domains go, are simple, and are in the unique position of also being easily understood by people unfamiliar with computer science, giving mazes more draw and utility. Mazes can be used as or within games, or even as art. The pursuit of easily accessible and robust mazes has lead to the development of a number of algorithms and approaches that uniquely generate mazes. It is important to have an intelligent tool that can

This literature review will cover research relating to maze generation, analysis, and maze representation. First, I will cover the common approach used for generating and representing mazes and the benefits that they bring, followed by a discussion of how genetic algorithms can be used to create mazes to users specifications. Next, I will cover the approaches and models that researchers have used to assess mazes. Next, I will cover research into alternative maze structures. I will conclude by covering possible future work in the area.

2 CELL GRAPHS

Mazes can be viewed as a graph of cells, where connected cells form passages through which an agent can navigate. According to Bellot et al, perfect mazes are defined as mazes that have a singular path connecting any two cells [1]. While not all mazes are required to have this attribute, it does allow for easy maze generation through the use of spanning tree generating algorithms [3]. As a result, maze generation typically makes use of existing algorithms for generating these spanning trees. However, these algorithms do not always generate mazes that are to the user's design parameters, so much of the field is focused on building more refined mazes that fit design specifications [4]. Kim, for example, proposes a designcentric method for maze generation that uses a set of attributes

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3 GENETIC ALGORITHM INTEGRATION

Frequently, when mazes have identifiable attributes that users find more desireable, they may integrate genetic algorithms into their maze generator algorithms. For example, Nagata et al. wanted to generate mazes where the solution path when filled in created an image [7]. They used a genetic algorithm to identify the best possible solution path for a given image before generating the rest of the maze around it. Similarly, this technique may be used to select for more difficult solution paths, and more difficult dead end paths.

4 CELLULAR AUTOMATA

Approaches that don't make use of spanning trees include the use of cellular automata to grow maze like structures. The cellular automata developed by Pech et al. generates mazes that are potentially usable for video game maps [8]. Their mazes are less tangled than others, and thus can be used in conjunction with image analysis techniques to train an evolutionary algorithm to more accurately generate mazes that fit their specifications. As cellular automata are based on the interaction between neighborhoods of cells, mazes lend themselves well to this format.

5 DIFFICULTY ANALYSIS

While difficulty is largely subjective, there are aspects of mazes that may cause them to be easier or harder than others. A maze that's solution is a straight line from the left side of the board to the right, with branches that lead away from this center line may still technically be a perfect maze, but it would not be considered difficult by human standards. This may not be the case for certain computer agent however. There are a few ways that mazes have been evaluated for difficulty, or interest. Bellot et al. uses a "fun" rating to rank mazes based more closely to how a human would evaluate a maze rather than a computer [1]. This approach takes into account how humans would scan the maze and other factors to evaluate mazes. Gabrovšek employs a technique based on using multiple different agents to determine how difficult mazes generated by different algorithms were [2]. McClendon produced an approach for defining a maze's difficulty and complexity based on the graph it produces [6]. This approach is, however, limited to perfect mazes.

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6 ATYPICAL MAZE REPRESENTATIONS

While mazes are typically generated and evaluated within square grids, there are other less traditional structures. While they generally retain a cell graph structure, the number of neighbors a cell has may fluctuate past the standard 2-4 seen in a rectangular board. Li and Mount, for instance, used a method to generate mazes on the surface of a sphere using randomly selected points grown into a complete graph [5]. Xu and Kaplan generate mazes that match the structures and shading of images they feed to their algorithm [9]. These mazes follow the contours of the images provided and thus do not have the standard grid structure seen in the other algorithms. They also outline techniques for offsetting curves to more closely match the images provided, as well as techniques for ensuring satisfyingly long solutions to any given puzzle.

7 CONCLUSION

This literature review discussed the state of the field of maze generation, particularly some of the general structures used to generate mazes, approaches used to analyze them, and outliers in the system that can make for interesting investigation. Spanning trees are used for generating perfect mazes, and genetic algorithms can be used to generate mazes with more specificity. Cellular automata can be used to create more loose maze structures that are more easily analyzed via image processing. The field remains open in the area of imperfect mazes, and the area of difficulty analysis remains open. There is yet no unified method for determining how challenging a maze is, and the metric will likely change whether a human is solving a maze, or a computer, and in the case of a computer, what method is being used to solve. Future research will entail refining measures of difficulty, and attempting to use the genetic techniques outlined in the existing works to accurately generate mazes that align with specific difficulty ratings. Additionally, there is room to investigate how cellular automata models would function in more constrained environments that may produce mazes that more closely resemble those generated in spanning tree based maze generators.

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