Flight Route Planner

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CS5011-P3

1 Introduction

The flight route planner system, created for the CS5011 module, leverages advanced AI search algorithms within "Oedipus," a simulated airspace constellation. This report examines the system's design, implementation, and effectiveness of various algorithms tailored to navigate this virtual airspace, constructed using a robust architecture of interconnected Java classes. Central to our exploration is the PolarGrid, a model based on polar coordinates that represent a uniquely segmented planetary system. This platform supports a range of algorithms, from basic methods like BFS and DFS to sophisticated, informed searches like BestF, AStar, and SMAStar, which are critical in determining the most efficient flight paths. This system's architecture is designed to be highly adaptable, allowing for extensive testing and evaluation of algorithm performance across diverse scenarios. This capability is essential not only for fulfilling the academic requirements of the CS5011 module but also for offering insights into real-world applications. These applications demonstrate the technology's potential in managing complex and dynamic environments such as airspace control.

2 Design and Implementation: System Overview

2.1 System Architecture Overview

The architecture of our flight route planner system is structured around multiple Java classes designed to interact seamlessly. These classes collectively facilitate the simulation of various flight route planning scenarios, employing different search strategies to navigate through a simulated airspace environment. This modular design ensures that each component functions independently yet integrates smoothly for comprehensive simulation performance.

2.2 Components

2.2.1 PolarGrid

At the heart of our system is the PolarGrid, a sophisticated model that simulates a planet using a polar coordinate system. This grid is characterised by:

– Grid Points: Defined by radial distances and angular coordinates, representing unique locations on the planet.

- Functionalities:
  - Validation: Ensures all points on the grid are within defined boundaries.
  - Movement Generation: Computes possible movements or neighbors based on current grid positions.
  - Cost Calculation: Determines the travel cost from one point to another, facilitating the evaluation of different path options.

2.2.2 Search Algorithms

Our system incorporates a diverse array of search algorithms, each encapsulated in separate classes to maintain clear functional boundaries:

- Uninformed Search Algorithms:
  - Breadth-First Search (BFS): Explores the broadest paths first to find the shortest path.
  - Depth-First Search (DFS): This technique delves deeper into the grid to explore all possible paths, which is helpful in complex search areas.
- Informed Search Algorithms:
  - Best-first Search (BestF): Prioritises the most promising paths based on a Euclidean distance heuristic.
  - A Search (AStar): Combines path costs with Euclidean heuristic estimates to find efficient routes.
  - Simplified Memory-bounded A (SMAStar): A memory-efficient variant of A* that uses a bounded memory approach.

These algorithms utilise the PolarGrid to determine viable paths from a starting point to a target, calculate movement costs, and effectively manage exploration states.

2.2.3 P3main

The P3main class serves as the entry point of the application. It processes command-line arguments to set up the simulation parameters, including the choice of search algorithm and grid configuration. The main functionalities include:

- Initialisation: Sets up the PolarGrid with specified dimensions and starting conditions.
- Execution: Launches the selected search algorithm to compute the flight path.
- Output: Generates results that include the optimal path found, the associated costs, and metrics such as the number of nodes visited.

3 Data Structures

3.1 Data Structures Used in the System

Our system employs various data structures, each chosen for its specific advantages in handling aspects of search algorithms and grid management:

- **ArrayLists:** Utilised within the `PolarGrid.getNeighbors` method to dynamically store and return lists of potential movements or neighboring nodes. Their flexibility is critical in grid areas where possible movements vary.
- **LinkedLists:** Serve dual purposes; they store paths in search algorithms like BFS and SMAStar. Particularly in BFS, LinkedLists allow for efficient path tracing by facilitating insertions at the list's beginning—essential for reconstructing the path from goal to start.
- **HashSets:** Track and ensure each node is visited only once across all searches, preventing redundant processing and cycles, which is crucial in maintaining efficiency in large grid environments.
- **HashMaps:** Associate each grid point with its corresponding node in the search space, accelerating access and supporting efficient path backtracking once the goal is reached.
- **Queues (LinkedLists):** Implement the FIFO (First In, First Out) principle in BFS to manage the exploration frontier, ensuring a systematic expansion of nodes.
- **TreeSets:** Employed in the SMAStar search to sort nodes by total cost, facilitating quick selection of the least costly node for subsequent exploration—a vital feature for enhancing the efficiency of cost-based search strategies.
- **AtomicIntegers:** Ensure safe node visit count increments across multiple threads or recursive calls, securing thread safety and count consistency.

4 Improved Section: Flow of Execution

4.1 System Operation Workflow

1. **Initialisation:** The process begins in `P3main`, which parses command-line arguments to configure the grid size, start and end points, and the selected search algorithm, setting the stage for simulation.
2. **Grid Setup:** A `PolarGrid` object is instantiated to serve as the environment for the search algorithms, defining the operational framework for subsequent actions.
3. **Algorithm Execution:** The appropriate search class is invoked based on user input. Each algorithm interacts with the grid to expand nodes, evaluate state conditions, and ultimately determine the most efficient path based on the algorithm's specific logic.
4. **Output:** Upon completion, the system outputs the search results, detailing the path's coordinates, the total cost involved, and the number of nodes explored. This output is formatted to align with the course's specifications and ensure the clarity of the presentation of the result.

5 Modular Design and Flexibility

This architecture supports modular implementation of various search strategies, allowing for easy adaptations or enhancements such as integrating additional algorithms or increasing grid complexity. The system is carefully designed to meet academic requirements and to ensure efficient, transparent operations.

6 Depth-First Search (DFS) Implementation

6.1 Algorithm Strategy

Depth-First Search (DFS) employs a "last-in, first-out" (LIFO) approach using a stack to manage node exploration. This strategy involves delving deeply into each path until it reaches a terminal node or an obstacle before backtracking. This method is particularly advantageous in complex environments like the simulated polar grid of the Oedipus constellation, where it is crucial to explore all potential paths to ascertain a viable route. DFS is highly memory-efficient and performs well in scenarios where the solution is close to the initial point; however, its efficiency diminishes as the search area expands.

6.2 Adaptation for the Polar Grid System

Each node is represented by a PolarPoint instance within the polar grid system, characterised by specific radial distances and angular coordinates. This setup is particularly conducive to navigating circular and segmented spaces like those in polar coordinate systems. During the DFS process, nodes are expanded by exploring neighboring points based on these coordinates. The expansion is constrained by the grid's boundaries, such as poles or the edges of the grid's defined size. The `expandNode` method strategically adds nodes to the stack in reverse order after sorting them by distance and angle from the current node, ensuring that the exploration always proceeds from the most recently discovered node.

6.3 Suitability for the Task

DFS is inherently thorough, making it highly suitable for environments where the primary goal is to ascertain the existence of a path rather than to find the shortest path. In the variable and often complex routes of the Oedipus airspace—marked by numerous obstacles and varying path conditions—DFS excels by ensuring that all potential paths are explored. This comprehensive exploration is crucial in confirming route feasibility in such challenging conditions. However, it is essential to note that the thoroughness of DFS comes at a cost. It may consume significant time and computational resources in larger search areas without guaranteeing the most efficient path.

7 Breadth-First Search (BFS) Implementation

7.1 Algorithm Strategy

Breadth-First Search (BFS) operates on a "first-in, first-out" (FIFO) principle, utilising a queue to manage the exploration of nodes systematically. This method involves exploring all neighboring nodes at the current depth level before advancing to the next, ensuring that the shortest path is found regarding the number of moves from the start to the goal. This characteristic makes BFS particularly effective for structured environments such as grid-based navigation systems like the polar grid.

7.2 Adaptation for the Polar Grid System

In the polar grid system, BFS stands out by expanding from a given node and exploring all possible movements, including those towards or away from the pole, and in both clockwise and counter-clockwise directions. It incorporates robust validity checks to comply with grid boundaries and to prevent invalid movements towards the poles. The efficient use of a queue in BFS ensures a layered and systematic exploration of the grid, optimising the pathfinding process to secure the shortest route within the structured confines of the Oedipus grid system.

7.3 Suitability for the Task

BFS's structured exploration methodology finds its ideal application in the flight route planner system, where promptly finding the most efficient route is crucial. By methodically exploring each level, BFS guarantees that the shortest path in terms of steps is the first viable solution identified, essential for optimising route planning in complex airspace management scenarios.

8 Conclusion

Both DFS and BFS have been adapted to meet the challenges of the polar grid system in the Oedipus constellation model. While DFS provides thorough exploration, making it suitable for scenarios where verifying the existence of any path is crucial, BFS excels in efficiently identifying the shortest path, making it highly applicable to practical applications such as flight routing. The selection of the appropriate algorithm can, therefore, be tailored based on the specific needs of the task—whether it is ensuring the existence of a path with DFS or optimising the path efficiency with BFS.

9 Design and Implementation of Informed Search Algorithms

9.1 Overview of Informed Search Algorithms

Informed search algorithms, such as Best-First Search, significantly enhance the search process by employing heuristics—strategies that estimate the cost from any given node to the goal. This approach is efficient in complex environments like the polar grid system, where the geometric nuances of the terrain obscure straightforward paths.

9.2 Best-First Search (BestF) Implementation

9.2.1 Algorithm Strategy

Best-First Search (BestF) optimises search efficiency by employing a heuristic-driven approach that systematically prioritises nodes based on their estimated cost to the goal. This method is powered by a crucial tool, the priority queue, which plays a pivotal role in managing the exploration process. It ensures that the most promising node, as determined by its heuristic value, is selected for expansion first.

9.2.2 Adaptation for the Polar Grid System

Node Representation: In the polar grid, each node is depicted as a PolarPoint, encapsulating its geographic positioning—radial distance and angular orientation—and its navigational data, including the cost accumulated from the start and the heuristic estimate towards the goal.

Heuristic Calculation: The heuristic is derived from the Euclidean distance formula, appropriately modified for polar coordinates. This adaptation allows the heuristic to reflect the actual travel distance more accurately by considering both radial and angular movement components.

Path Expansion: During path expansion, nodes assess their neighboring points based on permissible polar movements. Nodes that have not yet been explored or present a more cost-effective route than previously identified are added to the priority queue. This selective expansion ensures that the search is both directed and efficient.

9.2.3 Efficiency and Suitability:

Best-First Search excels in environments where the path to the goal requires rapid and effective navigation, making it ideally suited for applications such as route planning within the Oedipus airspace. The algorithm's ability to quickly hone in on the optimal path by accurately assessing heuristic information makes it invaluable for ensuring timely and efficient route determination.

10 A* Search Implementation

10.1 Algorithm Strategy

A* Search builds upon the principles of Best-First Search by integrating the heuristic estimate with the actual cost traveled from the starting node, employing a function $f(n) = g(n) + h(n)$. Here, $g(n)$ represents the cumulative path cost from the start to node n, and $h(n)$ is the heuristic estimate of the cost to reach the goal from n. This dual consideration effectively balances the need to explore new paths by exploiting promising paths and optimising the search process.

10.2 Adaptation for the Polar Grid System

10.2.1 Cost Calculation:

The path cost calculation considers radial and angular movement components in the polar grid system. This nuanced approach allows A* to adapt to the circular and segmented nature of the grid, where costs naturally escalate with increased distance from the pole and with significant angular deviations. This reflects the practical challenges of navigating such a specialised space.

10.2.2 Node Expansion:

A* expands on the principles of BestF by evaluating potential movements from each node and updating the path costs accordingly. It then recalculates the heuristic based on the new positions, continually refining the cost estimates to ensure that only the most promising paths are pursued.

10.2.3 Frontier Management:

The algorithm maintains a TreeSet that organises frontier nodes based on their total estimated costs ($f(n)$). This prioritisation ensures that the search always progresses from the least costly known path, thereby streamlining the discovery of the optimal route.

10.3 Efficiency and Suitability:

A* is renowned for its efficiency in discovering the shortest path in complex, structured environments such as polar grids. By balancing heuristic accuracy with actual travel costs, A* minimises unnecessary exploration, making it exceptionally suited for dynamic and critical applications such as air traffic control and advanced navigational systems.

11 Conclusion

Implementing informed search algorithms like Best-First Search and A* within the polar grid context underscores a sophisticated approach to tackling intricate pathfinding challenges. These algorithms excel by intelligently blending heuristic insights with tangible travel costs, optimising the search trajectory for efficiency and reliability. The choice between BestF and A* typically hinges on specific operational needs: BestF may prioritise speed in reaching a proximate goal, whereas A* focuses on delineating the shortest possible route, which is crucial for high-stakes decision-making environments.

12 Evaluation of Search Algorithms

12.1 Introduction

In artificial intelligence, the efficiency of pathfinding algorithms is critical, particularly for applications that navigate complex environments. The effectiveness of these algorithms is evaluated using a comprehensive set of performance metrics, which assess not only the quality of the paths they generate but also their computational efficiency. Detailed discussions on these metrics are included in the appendix for further reference.

12.2 Defining Performance Metrics

To systematically evaluate the performance of pathfinding algorithms, we use the following primary metrics:

- **Path Cost**: This metric quantifies the expense incurred moving from the start node to the goal node, incorporating both radial and angular components. This is particularly relevant in systems modelled using polar coordinates. For example:

  - **Radial Cost**: Measured as the absolute difference in radial distances between consecutive nodes.
  - **Angular Cost**: Calculated when nodes share the same radial distance; this involves computing a segment of the circle's circumference based on angular differences.

- **Nodes Visited**: Indicates the number of unique nodes the algorithm evaluates or visits during the search process. This metric directly indicates the algorithm's time complexity, reflecting the computational effort required to find a solution.
- **Maximum Frontier Size**: This represents the maximum number of nodes considered for expansion at any given point, illustrating the algorithm's space complexity. This metric is vital for understanding the memory demands imposed by the algorithm throughout its operation.
- **Execution Time**: Recorded in milliseconds, this metric captures the total time from the start of the search process to its completion. It is essential for evaluating the algorithm's suitability in real-time scenarios, where quick decision-making is paramount.

13 Comparison of Uninformed Search Algorithms: DFS vs. BFS

13.1 Overview

A comprehensive evaluation of Depth-First Search (DFS) and Breadth-First Search (BFS) provides insights into their performance through key metrics such as path cost, nodes visited, and execution time.

Depth-First Search (DFS): DFS is a depth-prioritised algorithm that explores the search space as deeply as possible before backtracking. This strategy can yield quick solutions but may lead to higher computational costs due to less efficient pathfinding:

- **Path Cost Variability:** DFS shows significant fluctuations in path costs, ranging from 4.356 to 117.029, reflecting its non-optimal path exploration.
- **Nodes Visited:** The number of nodes DFS explores varies widely, indicating inefficiency in scenarios where a solution only requires a partial path examination.

Breadth-First Search (BFS): In contrast, BFS systematically explores all neighboring nodes at the current depth before moving to the next, making it highly effective in scenarios requiring the shortest path discovery:

- **Consistent Lower Costs:** BFS generally achieves lower path costs and visits fewer nodes than DFS, exemplifying its efficiency.
- **Resource Management:** BFS's maximum frontier size is consistently smaller than DFS's, highlighting better memory and resource utilisation.

13.2 Conclusion

These observations suggest that BFS is more suitable for applications where finding the shortest path is critical, and space complexity can be managed. In contrast, DFS might be employed for quick searches in less complex environments.

14 Refined Section: Comparison of Informed Search Algorithms

14.1 Introduction

Analysing the performance of informed search algorithms like Best First Search (BestF) and A* Search (AStar) reveals distinct efficiency and path optimisation advantages.

Best First Search (BestF):

BestF employs a heuristic-based approach to prioritise nodes, which often results in efficient pathfinding with minimal node exploration:

- **Efficient Targeting:** BestF typically requires fewer nodes to reach a solution, as seen in scenarios like the path from 1:180 to 4:180, where it demonstrates effective heuristic utilisation despite only sometimes securing the shortest path.

A* Search (AStar): AStar enhances BestF's heuristic method by integrating the actual travel costs, yielding a balanced and often optimal pathfinding strategy:

- **Optimal Pathfinding:** AStar consistently finds shorter paths than BestF, evidenced by its performance in routes from 2:0 to 2:135, where it outperforms BestF in both nodes visited and execution times.

14.2 Conclusion

The comparison highlights AStar's superiority in achieving path optimality, making it preferable for scenarios where accuracy in cost and path efficiency is paramount. The choice between BestF and AStar will largely depend on the specific needs for speed versus precision in reaching the goal.

15 Discussion

15.1 Overview of Comparative Analysis

Our analysis reveals distinct operational characteristics and efficiencies of Depth-First Search (DFS), Breadth-First Search (BFS), Best First Search (BestF), and A* Search (AStar) under varied conditions. Understanding these nuances aids in selecting the most appropriate algorithm based on specific environmental constraints and performance objectives.

Depth-First Search (DFS): DFS is known for its depth-oriented exploration strategy, which, while effective in specific contexts, often results in higher path costs and varied performance:

- **Performance Variability:** In complex or large spaces, such as from node (4:0) to (7:90), DFS exhibited high path costs up to 60.480 and significant node visits, reflecting inefficiencies in extensive search areas.
- **Application Suitability:** DFS may be suited to applications where complete exploration is critical, such as environments requiring complete space mapping before decisions.

Breadth-First Search (BFS): BFS ensures the identification of the shortest path through methodical, level-wise exploration, effective in unweighted or uniformly weighted graphs:

- **Consistent Efficiency:** Demonstrated lower path costs and predictable performances, e.g., maintaining a maximum frontier size of 10 in the test from (9:225) to (2:45).
- **Resource Challenges:** Despite its pathfinding advantages, BFS can consume considerable resources in dense or vast areas, impacting its deployment in resource-constrained environments.

Best First Search (BestF): BestF uses heuristics to improve search efficiency, balancing quick pathfinding with resource usage:

- **Heuristic Reliance:** Efficiently navigates towards goals with fewer nodes visited, as seen from (1:180) to (4:180), depending on heuristic accuracy.
- **Performance Variability:** The effectiveness of BestF varies with the precision of the heuristic, affecting its reliability.

A* Search (AStar): AStar enhances the heuristic approach of BestF by incorporating actual travel costs, leading to optimal pathfinding:

- **Balanced Approach:** Combines cost and heuristic measures to optimise pathfinding, often resulting in the shortest and most cost-effective routes.
- **Superior Efficiency:** Consistently outperforms other algorithms in achieving optimal paths, as it effectively integrates both the heuristic foresight and the actual path costs.
- **Resource Optimisation:** While computationally more intensive than BestF, AStar provides a more reliable solution in complex environments where precision is crucial.

15.2 Strategic Implications and Recommendations

Each algorithm's effectiveness and suitability vary based on specific environmental needs, including the necessity for speed, space complexity, and available resources. Practitioners should consider:

- DFS for areas requiring exhaustive search without immediate efficiency concerns.
- BFS for scenarios demanding the shortest path with sufficient resources.
- BestF for environments where a precise heuristic can significantly streamline searches.
- AStar for complex scenarios where path cost and heuristic accuracy are critical for optimal performance.

15.3 Conclusion

This comparative analysis emphasises the importance of aligning algorithm strengths with specific application needs. Future implementations should tailor the search algorithm's choice to the problem domain's unique characteristics, ensuring optimal performance and efficient resource utilisation.

16 Appendix

17 DFS

Start	Goal	Cost	Nodes Visited	Max Frontier Size	Execution Time (ms)
2:0	2:135	4.356	27	14	21
1:180	4:180	11.639	23	14	20
1:315	4:45	16.352	21	14	19
3:90	0:0	-	32	14	20
1:135	5:315	51.124	25	21	19
4:0	7:90	60.480	30	24	20
6:270	0:45	-	56	25	23
9:225	2:45	12.142	53	33	24
2:45	9:225	117.029	42	30	22
7:270	7:90	52.841	29	28	21

18 BFS

Start	Goal	Cost	Nodes Visited	Max Frontier Size	Execution Time (ms)
2:0	2:135	4.712	15	9	17
1:180	4:180	3.000	16	8	17
1:315	4:45	4.571	26	8	20
3:90	0:0	Fail	32	9	24
1:135	5:315	7.927	48	8	21
4:0	7:90	9.283	46	14	21
6:270	0:45	Fail	56	12	20
9:225	2:45	13.283	71	10	22
2:45	9:225	13.283	72	10	22
7:270	7:90	21.991	32	14	21

19 BestF (Best First Search)

Start	Goal	Cost	Nodes Visited	Max Frontier Size	Execution Time (ms)
2:0	2:135	4.356	6	7	29
1:180	4:180	3.000	4	4	25
1:315	4:45	5.356	6	6	29
3:90	0:0	-	32	4	33
1:135	5:315	7.927	9	10	30
4:0	7:90	9.283	6	9	29
6:270	0:45	-	56	7	45
9:225	2:45	12.142	14	16	41

2:45	9:225	14.508	14	10	37
7:270	7:90	21.991	5	10	27

20 AStar

Start	Goal	Cost	Nodes Visited	Max Frontier Size	Execution Time (ms)
2:0	2:135	4.356	6	7	28
1:180	4:180	3.000	4	4	27
1:315	4:45	4.571	6	7	26
3:90	0:0	12.142	25	4	33
1:135	5:315	7.142	9	10	30
4:0	7:90	9.283	10	12	34
6:270	0:45	12.142	41	7	43
9:225	2:45	12.142	14	14	37
2:45	9:225	12.142	16	13	36
7:270	7:90	14.000	14	11	27