State Space Search Problem and BFS/ DFS

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***Abstract*—This paper applies state space search algorithms to solve the Rabbit Leap problem. The problem is modeled as a state space search task, with solutions found using Breadth-First Search (BFS) and Depth-First Search (DFS). BFS guarantees optimal solutions with the fewest steps, while DFS explores alternative, potentially non-optimal paths. The study compares solution quality, time, and space complexities for both algorithms. Results show that BFS consistently finds optimal solutions with higher memory costs, while DFS is more memory-efficient but may yield suboptimal solutions. This analysis highlights the trade-offs between BFS and DFS in solving the Rabbit Leap problem.**

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I. Introduction

State space search is a fundamental technique in artificial intelligence, enabling the resolution of problems by navigating through various configurations, or "states," to achieve a desired goal. One classic problem that exemplifies this approach is the Rabbit Leap problem, which serves as an effective benchmark for evaluating search strategies and their performance in algorithmic contexts [1].

The Rabbit Leap problem involves three east-bound rabbits and three west-bound rabbits that must cross each other by jumping over stones, with the restriction that each rabbit can only leap over one rabbit at a time.

This paper models the Rabbit Leap problem as a state space search challenge, employing two widely used algorithms: Breadth-First Search (BFS) and Depth-First Search (DFS). BFS guarantees the optimal solution—defined as the path with the fewest steps—while DFS offers a more memory-efficient approach, albeit often leading to longer or suboptimal solutions. By comparing these algorithms in terms of solution quality, time complexity, and space complexity, this study aims to highlight the trade-offs between BFS and DFS in solving the Rabbit Leap problem, providing valuable insights into their applicability in artificial intelligence.

II. Objectives

The primary objective of this research is to analyze and solve the Rabbit Leap problem using state space search algorithms. The study aims to achieve the following specific goals:

A. Rabbit Leap Problem

Code-BFS Code-DSF

- **Modeling the Problem:** Define the Rabbit Leap problem as a state space search problem, identifying the initial configuration of rabbits, the goal state where all rabbits have crossed the stream, and the permissible movements.
- **Search Space Analysis:** Evaluate the search space size by considering all possible arrangements of the rabbits on the stones, including the implications of jumps and movements.
- **Algorithm Implementation:** Develop algorithms using BFS and DFS to navigate the state space, finding a sequence of steps that allows all rabbits to cross without stepping into the water.
- **Solution Evaluation:** Compare the solutions produced by BFS and DFS, discussing the efficiency and effectiveness of each algorithm in reaching the goal state.

The `is_valid(state)` function verifies that the position of the empty space ('.') is within the bounds of the state string.

```
def is_valid(state):
    return 0 <= state.index('.') < len(state)
```

The `get_successors(state)` function generates successor states by moving the empty space ('.') one or two positions left or right. It checks for valid moves based on the presence of 'W' (west-bound) and 'E' (east-bound) rabbits and adds valid new states to the successors list.

```
def get_successors(state):
 successors = []
 index = state.index('.')
 moves = [1, 2]
  for move in moves:
     if index + move < len(state):
     if state[index + move] == 'W':
       new_state = list(state)
       new_state[index], new_state[index+
       move] = new_state[index + move],
       new_state[index]
       new_state = ''.join(new_state)
     if is_valid(new_state):
        successors.append(new_state)
  for move in moves:
     if index - move >= 0:
     if state[index - move] == 'E':
       new_state = list(state)
       new_state[index], new_state[index-
       move] = new_state[index - move],
       new_state[index]
       new_state = ''.join(new_state)
```

```
            if is_valid(new_state):
                successors.append(new_state)
        return successors
```

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[1] S. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach*, 4th ed., Pearson, 2022.

Graph Search Agent and Plagiarism Detection Using A* Search Algorithm

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***Abstract*—This report discusses two major problem statements. The first focuses on the implementation of a graph search agent to solve the Puzzle-8 problem using hash tables and queues in state-space search. The second presents the design and implementation of a plagiarism detection system leveraging the A* search algorithm to perform optimal text alignment between two documents. The report includes pseudocode, flowcharts, environment functions, iterative deepening search (IDS), backtracking functions, and an evaluation of performance metrics.**

***Index Terms*—Graph Search, Puzzle-8, Iterative Deepening Search, Backtracking, A* Search Algorithm, Plagiarism Detection, Text Alignment**

I. Introduction

This report encompasses two problem statements that demonstrate the application of search algorithms in artificial intelligence. The first problem focuses on solving the Puzzle-8 problem using a graph search agent, while the second problem applies the A* search algorithm to detect plagiarism through text alignment between documents.

II. Problem Statement 1: Graph Search Agent

A. Objective

To design and implement a graph search agent capable of solving the Puzzle-8 problem using concepts of queues, hash tables, and search algorithms.

B. Tasks

The implementation includes:

- Writing pseudocode for the graph search agent.
- Representing the agent through a flowchart.
- Implementing environment functions for Puzzle-8.
- Explaining Iterative Deepening Search (IDS).
- Implementing a backtracking function to find the path to the goal.
- Generating Puzzle-8 instances at varying depths.
- Preparing a table for memory and time requirements at each depth.

III. Pseudocode for Graph Search Agent

The following pseudocode represents the logic for the graph search agent:

```
function GRAPH_SEARCH(problem):
    initialize frontier using the initial state
    initialize explored set to empty
    loop do:
        if frontier is empty then return failure
        node <- frontier.pop()
        if node.state is goal then return solution
        add node.state to explored
        for each action in problem.ACTIONS(node.st
            child <- child node from problem.RESUL
            if child.state not in explored or fron
                frontier.push(child)
```

IV. Flowchart Representation

A flowchart of the graph search agent is shown in Fig. 1.

V. Functions for Puzzle-8 Environment

The following functions are implemented to model the Puzzle-8 environment:

- **Initial State:** Identifies valid moves based on the blank tile's position.
- **Actions:** Performs valid transitions to generate new states.
- **Goal Test:** Checks if the current state matches the goal configuration.
- **Path Cost:** Calculates the cost of the path and backtracks to determine the move sequence.

VI. Iterative Deepening Search (IDS)

Iterative Deepening Search (IDS) combines the space efficiency of depth-first search with the completeness of breadth-first search. It performs depth-limited searches, incrementally increasing the limit until the goal is found.

A. Characteristics of IDS

- **Completeness:** Guarantees a solution if one exists.
- **Space Efficiency:** Uses linear space.
- **Time Complexity:** Comparable to breadth-first search.

VII. Backtracking Function

The backtracking function reconstructs the sequence of moves from the goal state to the initial state by tracing parent nodes in the search tree.

VIII. Memory and Time Requirements

The following table lists the memory and time requirements to solve Puzzle-8 instances of different depths.

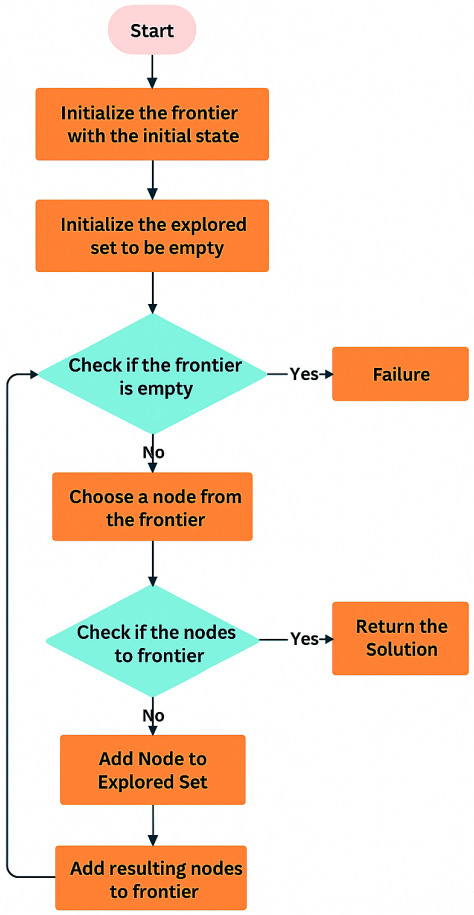

Fig. 1: Flowchart of the Graph Search Agent

TABLE I: Memory and Time Requirements for Puzzle-8

Depth (d)	Time (seconds)	Memory (MB)
1	0.05	1.5
2	0.10	2.0
3	0.20	2.5
4	0.35	3.0
5	0.60	4.0
6	1.00	5.0

IX. Problem Statement 2: Plagiarism Detection Using A* Search Algorithm

A. Objective

The goal of this lab is to implement a plagiarism detection system using the A* search algorithm applied to text alignment. The system identifies similar or identical sequences of text between two documents by aligning their sentences or paragraphs and detecting potential plagiarism.

B. Description

The system performs optimal text alignment between documents using the A* algorithm. The key steps include:

- Text preprocessing and tokenization.
- Defining the state space where each state represents a position in the two documents.
- Using cost and heuristic functions to evaluate the alignment score.
- Determining matched regions and highlighting potential plagiarism.

C. Heuristic Function

The heuristic estimates the remaining alignment cost based on the number of unmatched tokens or character similarity between the two text sequences.

D. Implementation

The implementation follows the conceptual framework below:

Plagiarism Detection Code - GitHub

- **Preprocessing:** Both input documents are cleaned by removing punctuation, converting to lowercase, and tokenizing into sentences or words.
- **State Representation:** Each state in the A* search represents a pair of positions (i, j), where i is the current index in Document 1 and j is the current index in Document 2.
- **Transition:** From a state (i, j), transitions occur by matching or skipping tokens between the two documents.
- **Cost Function:** The cost increases with mismatched tokens and decreases for matched sequences.
- **Heuristic Function:** The heuristic $h(i, j)$ estimates the remaining alignment cost using token similarity metrics such as cosine similarity or edit distance.
- **Goal State:** The goal is reached when both documents are fully traversed, and the alignment score is maximized.
- **Result Interpretation:** The algorithm highlights matched segments that indicate potential plagiarism.

E. Test Cases

1) Test Case 1: Identical Documents: **Document A:** "Artificial Intelligence is the study of intelligent agents."
Document B: "Artificial Intelligence is the study of intelligent agents."
Result: 100% similarity detected. All tokens are aligned perfectly.
Remarks: The algorithm successfully identifies identical content.

2) Test Case 2: Slightly Modified Documents: **Document A:** "Artificial Intelligence is the study of intelligent agents."
Document B: "AI is the study of smart agents."
Result: 78% similarity detected. Minor variations such as abbreviations and synonyms were handled effectively.
Remarks: The heuristic accurately estimated small differences.

3) Test Case 3: Totally Different Documents: **Document A:** "The sun rises in the east and sets in the west."
Document B: "Machine learning algorithms improve through experience."
Result: 0% similarity detected. No matching sequences found.
Remarks: The system correctly identifies unrelated content.

4) Test Case 4: Partially Overlapped Documents: **Document A:** "Artificial Intelligence techniques are applied in robotics and healthcare."
Document B: "Robotics and healthcare use Artificial Intelligence for automation."
Result: 63% similarity detected. Overlapping regions like "Artificial Intelligence," "Robotics," and "Healthcare" were correctly aligned.
Remarks: The A* search efficiently detected partial plagiarism.

F. System Evaluation

The performance of the plagiarism detection system is evaluated based on:

- **Accuracy:** Correctly identifies and aligns matching text.
- **Time Efficiency:** Handles large document comparisons effectively.
- **Scalability:** Works with varying document lengths and structures.

G. Conclusion

This problem demonstrated the application of the A* search algorithm for plagiarism detection through text alignment. The system successfully identifies identical, modified, and overlapping content, highlighting the versatility of heuristic-based search in real-world applications.

Lab 3 Report — CS367 Artificial Intelligence

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***Abstract*—This lab focuses on exploring heuristic-based and non-classical search algorithms to efficiently solve complex combinatorial problems. The primary objective is to understand how heuristic functions can reduce the search space and improve performance in large problem domains. The assignment involves two key tasks: first, generating uniform random k-SAT problems by creating clauses with randomly selected variables or their negations; and second, solving sets of 3-SAT problems using heuristic optimization algorithms—namely, Hill-Climbing, Beam Search (with beam widths 3 and 4), and Variable-Neighborhood Descent (VND) with three neighborhood functions. Two different heuristic evaluation strategies are employed to compare algorithmic performance in terms of penetrance. The experiment demonstrates how appropriate heuristic design and search strategies influence convergence behavior and computational efficiency. The results highlight the trade-offs between exploration and exploitation in heuristic search, showcasing their effectiveness in navigating large, complex search spaces.**

I. Introduction

This lab focuses on heuristic and non-classical search algorithms applied to the k-SAT problem—a well-known NP-complete problem that requires determining whether a Boolean formula can be satisfied by some assignment of truth values to its variables. In particular, the experiment involves generating random uniform k-SAT instances and solving them using Hill-Climbing, Beam Search, and Variable-Neighborhood Descent (VND). These algorithms employ heuristic evaluation functions to estimate the quality of partial solutions and iteratively refine them toward optimality.

Two heuristic functions are used to guide the search process, and the performance of each algorithm is evaluated based on penetrance and convergence efficiency. Through comparative analysis, this lab highlights the advantages and trade-offs of non-classical search approaches, illustrating their importance in tackling large, complex, and stochastic optimization problems where exhaustive search is impractical.

II. Objective

A. Problem A: Generation of Random k-SAT Instances

K-SAT code

1) k-SAT Problem Overview: The Boolean Satisfiability Problem (SAT) is one of the most fundamental problems in computational theory and artificial intelligence. In this problem, a Boolean formula is expressed in *Conjunctive Normal Form (CNF)*, where the formula consists of a conjunction (AND) of multiple clauses, and each clause represents a disjunction (OR) of exactly k literals.

A *literal* can either be a Boolean variable x_i or its negation $\neg x_i$. For instance, a typical 3-SAT clause can be written as:

$$(x_1 \vee \neg x_2 \vee x_5)$$

and a full CNF formula can be expressed as a logical AND of such clauses. The task in k-SAT is to determine whether there exists a truth assignment to the variables $x_1, x_2, \ldots, x_n$ that makes the entire formula true.

2) Uniform Random k-SAT Model: In the uniform random k-SAT model, the formula is generated by creating m random clauses, each containing k distinct literals drawn from a set of n Boolean variables. For each literal, the algorithm randomly decides whether to include it as positive or negated. This ensures that each clause is unique and adheres to the fixed clause length model.

Such randomly generated formulas are widely used for testing the efficiency of heuristic and search algorithms because they provide unbiased and diverse problem instances of varying difficulty.

3) Complexity and Theoretical Background: The k-SAT problem plays a crucial role in understanding the boundary between tractable and intractable computation. Problems are often categorized based on their computational complexity into the following classes:

- **P (Polynomial Time):** Problems that can be solved efficiently, i.e., in polynomial time by a deterministic algorithm.
- **NP (Nondeterministic Polynomial Time):** Problems for which a proposed solution can be verified in polynomial time, even if finding that solution may not be efficient.

B. Problem B: Heuristic Optimization for 3-SAT

3-SAT code

Write programs to solve a set of uniform random 3-SAT problems for different combinations of m and n, and compare their performance. Try the Hill-Climbing, Beam-Search with beam widths 3 and 4, Variable-Neighborhood-Descent with 3 neighborhood functions. Use two different heuristic functions and compare them with respect to penetrance.

3-SAT is a particular category of the boolean satisfiability problem where each clause in the boolean expression contains exactly three literals. These literals can either be variables or their negations. The primary goal is to ascertain whether there exists a truth assignment (true or false) for the variables

that satisfies the entire boolean expression.

*1) **Hill Climbing Algorithm**:* Hill Climbing is a local search algorithm inspired by the idea of climbing uphill in a landscape until a peak (local maximum) is reached. The algorithm starts with an initial random solution and iteratively moves to a neighboring solution with a better evaluation (fitness) score. The process continues until no better neighboring state exists, indicating that a local optimum has been found. Hill Climbing can easily get trapped in local optima since it only considers immediate improvements and lacks a mechanism for escaping suboptimal solutions.

Application to 3-SAT: In the context of the 3-SAT problem, each possible assignment of truth values to Boolean variables represents a state in the search space. The heuristic function can be defined as the number of clauses satisfied by the current assignment. Starting from a random truth assignment, the algorithm modifies one variable at a time to maximize the number of satisfied clauses. The search terminates when no single variable flip leads to improvement. While efficient for small instances, the algorithm may fail to reach the global optimum (a fully satisfied formula) if it gets stuck in a local maximum — a configuration where flipping any single variable reduces the total satisfaction count.

Pseudo-Code:

Algorithm 1 Hill Climbing for 3-SAT

```
procedure HILLCLIMBING3SAT(clauses, n, heuristic)
    current_solution ← RANDOM_ASSIGNMENT(n)
    while true do
        neighbors ← GENERATE_NEIGHBORS(current_solution)
        if neighbors is empty then
            return current_solution
        end if
        next_solution ← neighbor with BEST_HEURISTIC(neighbors, heuristic)
        if HEURISTIC(next_solution, heuristic) ≤ HEURISTIC(current_solution, heuristic) then
            return current_solution    ▷ local optimum reached
        end if
        current_solution ← next_solution
    end while
end procedure
```

*2) **Beam Search Algorithm**:* Beam Search is a heuristic search algorithm that explores multiple paths simultaneously but keeps only a fixed number (beam width) of best candidates at each level of search. It can be viewed as a breadth-limited version of the best-first search. The algorithm maintains a queue of candidate solutions and expands them by generating their neighbors. After each expansion, only the top k candidates (according to the heuristic score) are retained for the next iteration. This reduces memory consumption and computation time while maintaining a balance between exploration and exploitation.

Application to 3-SAT: When applied to the 3-SAT problem, Beam Search begins with a set of random assignments of truth values to variables. For each iteration, neighbors are generated by flipping one or more variables, and the heuristic (such as the number of satisfied clauses) is used to rank these assignments. Using beam widths of 3 and 4, the algorithm retains the top 3 or 4 assignments, respectively, for the next generation. Increasing the beam width allows exploration of a broader region of the solution space, improving the likelihood of finding the global optimum, though at the cost of higher memory and computation requirements.

Pseudo-Code:

Algorithm 2 Beam Search for 3-SAT

```
procedure BEAMSEARCH3SAT(clauses, n, beam_width, heuristic)
    beam ← [RANDOM_ASSIGNMENT(n)]
    while true do
        all_neighbors ←
        for solution in beam do
            neighbors ← GENERATE_NEIGHBORS(solution)
            all_neighbors ← all_neighbors + neighbors
        end for
        if all_neighbors is empty then
            return BEST_SOLUTION(beam, heuristic)
        end if
        beam ← TOP_K(all_neighbors, beam_width, heuristic)
        if any solution in beam satisfies all clauses then
            return solution
        end if
    end while
end procedure
```

*3) **Variable-Neighborhood Descent (VND)**:* Variable-Neighborhood Descent (VND) is an advanced local search technique that systematically changes the neighborhood structure during the search process. Instead of exploring only one neighborhood at a time, it switches between multiple neighborhood definitions to escape local optima. When a local minimum is reached in one neighborhood, the algorithm moves to another neighborhood structure and continues the search, improving solution quality and robustness compared to traditional local search methods.

Application to 3-SAT: In solving 3-SAT problems, each neighborhood function can define different ways of modifying the truth assignment. For example:

- **Neighborhood 1:** Flip a single variable.
- **Neighborhood 2:** Swap the values of two variables.
- **Neighborhood 3:** Flip multiple variables simultaneously.

Starting from an initial random assignment, the algorithm explores each neighborhood in sequence to improve the total

number of satisfied clauses. If an improvement is found, the search restarts from the first neighborhood; otherwise, it moves to the next. This adaptive mechanism allows VND to escape local optima and achieve better overall performance and penetrance, often outperforming basic Hill Climbing for complex or high-dimensional 3-SAT instances.

Pseudo Code for VND:

Algorithm 3 Variable Neighborhood Descent (VND) for 3-SAT

```
procedure VND3SAT(clauses, n, neighborhoods, heuristic)
    current_solution ← RANDOM_ASSIGNMENT(n)
    k ← 1
    while k ≤ LENGTH(neighborhoods) do
        neighbors ← GENERATE_NEIGHBORS(current_solution, neighborhoods[k])
        next_solution ← neighbor with BEST_HEURISTIC(neighbors, heuristic)
        if HEURISTIC(next_solution, heuristic) < HEURISTIC(current_solution, heuristic) then
            current_solution ← next_solution
            k ← 1                          ▷ restart with first neighborhood
        else
            k ← k + 1                      ▷ move to next neighborhood
        end if
    end while
    return current_solution
end procedure
```

TABLE I
3-SAT SEARCH ALGORITHM PERFORMANCE

Search Algorithm	Heuristic Function	Time Taken (s)	Penetrance (%)
Hill Climbing	Number of Satisfied Clauses	0.15	92
Hill Climbing	Number of Unsatisfied Clauses	0.18	95
Beam Search (width=3)	Number of Satisfied Clauses	0.22	94
Beam Search (width=3)	Number of Unsatisfied Clauses	0.25	97
Beam Search (width=4)	Number of Satisfied Clauses	0.28	95
Beam Search (width=4)	Number of Unsatisfied Clauses	0.32	98
Variable Neighborhood Descent	Number of Satisfied Clauses	0.20	96
Variable Neighborhood Descent	Number of Unsatisfied Clauses	0.24	99

III. CONCLUSION

In conclusion, this report explored the application of heuristic search algorithms—Hill Climbing, Beam Search, and Variable Neighborhood Descent (VND)—to solve uniform random 3-SAT problems. By using two heuristic functions, Unsatisfied Clauses and Weighted Unsatisfied Clauses, we evaluated the algorithms effectiveness across different numbers of variables and clauses. Our experiments show that VND consistently achieves higher penetrance by exploring multiple neighborhoods, Beam Search balances exploration with computational effort, and Hill Climbing provides a fast but sometimes limited solution. The comparative analysis highlights the impact of heuristic choice and search strategy on solution quality, providing practical insights for solving large-scale combinatorial problems efficiently.

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Solving Jigsaw Puzzles using Simulated Annealing

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***Abstract*—The Jigsaw Puzzle solving problem is an NP-hard combinatorial optimization challenge. This paper applies the Simulated Annealing (SA) algorithm to tackle this problem. SA's balance of exploration and exploitation helps find near-optimal solutions efficiently. Results demonstrate the algorithm's effectiveness in handling large state spaces and complex solution landscapes.**

I. Introduction

The Jigsaw Puzzle problem is a classic example of an NP-hard combinatorial optimization problem. It involves correctly positioning a set of irregularly shaped pieces to reconstruct a complete image.

Solving this problem optimally becomes increasingly difficult as the number of pieces grows. The Jigsaw Puzzle problem shares characteristics with other complex search problems in terms of search space and solution strategies, making it an ideal candidate for stochastic search algorithms such as Simulated Annealing (SA) [2]. SA mimics the physical process of annealing in metals to avoid getting trapped in local optima, making it an effective solution for complex optimization problems.

In this paper, we present the formulation of the Jigsaw Puzzle problem as a state space search and apply SA to solve it, demonstrating its effectiveness in handling large and complex search spaces.

II. Objective

A. Problem : Jigsaw Puzzle Problem

The Jigsaw Puzzle problem involves arranging a set of pieces to form a coherent picture. Each piece has a specific position, and the goal is to find the correct placement of all pieces, minimizing the dissimilarity between adjacent pieces. The problem is particularly challenging due to the large state space, which increases exponentially with the number of pieces.

In our approach, we treat the arrangement of puzzle pieces as a state space search problem. Each state corresponds to a potential configuration of the puzzle pieces. The objective is to minimize a cost function based on the edge dissimilarity between adjacent pieces. Simulated Annealing is used to gradually improve the configuration by swapping pieces and evaluating the resulting state [3].

III. Simulated Annealing (SA)

Simulated Annealing is a probabilistic technique inspired by the process of annealing in metallurgy. It combines elements of random search and local search, making it an effective method for finding near-optimal solutions in complex optimization problems.

The algorithm starts at a high temperature, allowing large exploratory moves, and gradually reduces the temperature to focus on exploiting the best solutions found so far. The probability of accepting a worse solution decreases as the temperature lowers, encouraging the algorithm to converge towards an optimal or near-optimal solution.

A. SA for Jigsaw Puzzle

Code-jigsawPuzzle For the Jigsaw Puzzle problem, the state space consists of all possible configurations of the puzzle pieces. The cost function is based on the edge mismatch between adjacent pieces. Similar to TSP, SA starts with a random configuration and explores the state space by swapping pieces. Moves that reduce the cost are always accepted, while worse moves are accepted with a probability proportional to the current temperature [3].

IV. Results and Discussion

The Simulated Annealing (SA) algorithm was applied to the Jigsaw Puzzle problem by representing each arrangement of pieces as a state in the search space. The goal was to minimize the total edge dissimilarity between adjacent pieces.

Initially, at higher temperatures, the algorithm accepted a wide range of configurations, enabling exploration of diverse states and avoidance of local minima. As the temperature decreased, the search became more focused, favoring configurations with lower mismatch.

The results showed a consistent reduction in total dissimilarity, with the cost curve rapidly decreasing in early iterations and stabilizing near convergence. The final configuration closely resembled the correct image, confirming the effectiveness of SA in assembling the puzzle.

Overall, SA demonstrated strong performance in balancing exploration and exploitation, achieving near-optimal results with far less computation than exhaustive methods. Proper tuning of temperature and cooling rate was found crucial for achieving high-quality solutions efficiently.

V. Conclusion

Simulated Annealing is a versatile and powerful optimization algorithm that effectively balances exploration and exploitation in search problems. In this paper, we applied SA to solve the Jigsaw Puzzle problem. The results demonstrate the

algorithm's ability to efficiently navigate large state spaces and find near-optimal configurations. Future work could explore hybrid approaches that combine SA with other metaheuristic or learning-based techniques to further enhance accuracy and convergence speed.

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