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### Experiment # 5: Implement stochastic Hill climbing Algorithm for Robot path finding

#### Aim/Objective:

Implementing a stochastic Hill climbing Algorithm for Robot path finding

#### Description:

Students will learn the Stochastic Hill Climbing (SHC) which is a local search algorithm commonly used in optimization problems, including pathfinding for robots in dynamic environments.

#### Pre-Requisites:

- Students will be well-equipped to understand, implement, and customize the Stochastic Hill Climbing algorithm for robot pathfinding effectively.
- Familiarity with programming concepts and basic knowledge of Python programming language

#### Pre-Lab:

- What is Stochastic Hill Climbing?

Stochastic Hill climbing is an optimization technique, where instead of always choosing the best nearby option, the algorithm randomly picks a neighbour. It can help avoid getting stuck in local peaks by introducing randomness into search.

- How does Stochastic Hill Climbing differ from regular Hill Climbing?

Stochastic Hill climbing differs from regular hill climbing in that it is randomly selecting a neighbouring solution instead of always picking the best one. This randomness can help avoid getting stuck in loops.

- What are the advantages of using Stochastic Hill climbing for pathfinding?

for pathfinding by getting stuck in introducing random to explore more

- What are the key components of pathfinding?

1. Initial Point

2. Step Size

3. Randomness

4. Sideways

5. Avoid

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3. What are the advantages of using Stochastic Hill Climbing for robot pathfinding?

Stochastic hill climbing is useful for robot pathfinding because it helps the robot avoid getting stuck in sub optimal path by introducing randomness. This allows the robot to explore more potential routes.

4. What are the key components required to implement Stochastic Hill Climbing for robot pathfinding?

1. Initial Point: Start with an initial point in the search point

2. Step Size: Define a step size, which represents the distance within the search space.

3. Randomness: Generate a new point within the step size distance of the initial point

4. Sideways Moves: Allow exploration across flat regions by accepting different points

5. Avoid Infinite loops: Limit consecutive sideways moves to prevent infinite loops

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### In-Lab:

A robot is located in a grid of size  $n \times m$ . The robot can move up, down, left, or right, but cannot move through obstacles. The goal is to find a path from the start position to the goal position using a stochastic hill climbing algorithm.

### Stochastic Hill Climbing:

1. **Initial State:** Start at the initial position.
2. **Neighbor Selection:** Randomly choose one of the neighboring states.
3. **Evaluation:** Move to the chosen neighboring state if it improves the evaluation function.
4. **Termination:** Stop when the goal is reached or no better neighbors are found.

### Evaluation Function

The evaluation function for the hill climbing algorithm can be the Manhattan distance to the goal: Manhattan Distance =  $|x_1 - x_2| + |y_1 - y_2|$  where  $(x_1, y_1)$   $(x_2, y_2)$  are the coordinates of the current position and are the coordinates of the goal.

### Procedure/Program:

import random

def distance(a, b):

return abs(a[0] - b[0]) + abs(a[1] - b[1])

def stochastic\_hill(start, goal, n, m, obstacles):

current = start

while current != goal:

neighbors = [(current[0], current[1])]

for dx, dy in [(-1, 0), (0, 1), (0, -1), (1, 0)]

neighbor = [pos for pos in neighbors if

$0 \leq pos[0] \leq n$  and  $0 \leq pos[1] \leq m$  and

pos not in obstacles].

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```

next_move = random.choice(neighbors)
if distance(next_move, goal) < distance(current):
    current = next_move
else:
    break
return current

```

- Data and Results:

The output of the above program tells that the robot has reached the goal position ~~(1,1)~~ by using this technique.

- Analysis and Inferences:

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The algorithm efficiently navigates the grid by moving towards the goal using randomness to avoid local minima.

It helps to stop eagerly if no better moves are available, leading to suboptimal paths.

This random restarts can improve the performance in complex grids.

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2) Ensure optimal path using annealing and heating schedule

3) Advantage: Simple

Drawbacks: Slower

be

4) Handle local maxima using random restarts and simulated annealing techniques

5) Stochastic Hill Climbing

Obstacle filled environment

methods might get stuck

#### VIVA-VOCE Questions (In-Lab):

1. What is the stochastic hill climbing algorithm, and how does it differ from deterministic hill climbing?
2. How do you ensure that the robot finds an optimal path using the stochastic hill climbing algorithm?
3. What are the advantages and potential drawbacks of using stochastic hill climbing for pathfinding in a robotic environment?
4. How do you handle local maxima, plateaus, and ridges in the context of the hill climbing algorithm?
5. Can you explain a scenario where stochastic hill climbing would be more effective than other pathfinding algorithms?

#### Post-Lab:

Place N queens on an N×N chessboard in a random configuration and use stochastic hill climbing to solve it. This reduces the number of conflicts.

Description: Stochastic hill climbing is a local search algorithm for optimization problems. It introduces randomness into the search process. In this problem move a queen to an adjacent square.

- Procedure/Program:
 

```
import random
def conflicts(queen):
    conflicts = 0
    for i in range(len(queen)):
        for j in range(i+1, len(queen)):
            if queen[i] == queen[j] or abs(queen[i] - queen[j]) == abs(i - j):
                conflicts += 1
    return conflicts
```

1. Stochastic Hill climbing randomly picks a neighbour to move to if it's better, unlike deterministic Hill Climbing which always chooses the best neighbour.

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2) Ensure optimal pathfinding by using random restarts, annealing and heuristics to guide move and avoid local optima.

3) Advantage: Simple avoids local optima.

Drawbacks: Slower, possible, inefficiency, may miss best path.

4) Handle local maxima plateaus and ridges with random restarts. small perturbations and look ahead techniques.

5) Stochastic Hill Climbing excels in complex, abstract obstacle filled environments when determine methods might fail.

#### Post-Lab:

Place N queens on an  $N \times N$  chessboard so that no two queens threaten each other by starting with a random configuration and use stochastic hill climbing to move a queen to a new position if it reduces the number of conflicts.

Description: Stochastic hill climbing is a variant of the hill climbing algorithm used in optimization problems. It introduces randomness into the selection of the next move, which can help avoid local maxima. In this problem move a queen to a new position so that it reduces the number of conflicts.

- Procedure/Program:

```
import random
def conflicts(board):
    return sum([board[i] == board[j] or abs(i - j) == abs(board[i] - board[j]) for i in range(len(board)) for j in range(i + 1, len(board))])
```

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$\text{board}[i] - \text{board}[j] = j - i$  for  $j$  in range( $i+1, \text{len}(\text{board})$ )

for  $j$  in range( $\text{len}(\text{board})$ ):

def stochastic\_hill\_climb( $n$ ):

$\text{board} = [\text{random.randint}(0, n-1)]$

for  $i$  in range( $n$ ):

while True:

current = conflicts( $\text{board}$ )

if current == 0:

return  $\text{board}$

col = random.randint(0,  $n-1$ )

move = [conflicts( $\text{board}[:, \text{col}] + \text{rows} +$

$\text{rows}[:, \text{col} + i :]$ ] for

$i$  in range( $n$ )

best\_row = min(move)

$\text{board}[\text{col}] = \text{best\_row}$

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- Data and Results

The problem is iterative

- Analysis and

board

Conflict

Evaluator Remark (if applicable)

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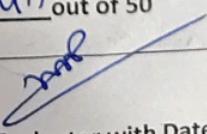
- Data and Results:

The stochastic hill climbing algorithm for the N-Queens problem starts with a random board configuration and iteratively moves a queen to reduce conflicts.

- Analysis and Inferences:

Calculate the number of conflicts for current board configuration

Moves a random queen to saw that minimizes conflicts continuing until no conflicts remain

Evaluator Remark (if Any):	Marks Secured: <u>47</u> out of 50  
Signature of the Evaluator with Date	