Autonomous Exploration System for Volcanic Terrain Using MDP

CSE440 - Artificial Intelligence | Group 5 - Section 1 | Faculty: MSRB

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Summary

This report presents a Markov Decision Process (MDP) formulation for autonomous volcanic terrain exploration. The system balances safety and efficiency through mathematical modeling of sequential decision-making in unpredictable volcanic environments.

MDP Formulation

State Space (S): Grid-based discrete positions $S = \{(x,y) \mid 0 \leq x,y < grid\_size\}$ with $|S| = 25$ for 5×5 grid.

Action Space (A): Four directional movements A = {NORTH, SOUTH, EAST, WEST} with $|A| = 4$.

Transition Function T(s'|s,a): Deterministic transitions where $T(s'|s,a) = 1$ for valid moves, 0 otherwise. Boundary conditions keep agent in current state.

Reward Function R(s,a,s'): Terrain-based rewards:

- Goal state: +100
- Safe terrain: -1
- Gas emission: -50
- Crater: -75
- Lava flow: -100

Discount Factor (γ): $\gamma = 0.9$ balancing immediate vs. future rewards.

Policy Implementation

Heuristic Strategy: Goal-oriented movement using simple decision rules:

python

```python
def policy(state):
    x, y = state
    goal_x, goal_y = grid_size-1, grid_size-1

    if x < goal_x and y < goal_y:
        return random.choice([SOUTH, EAST])
    elif x < goal_x:
        return SOUTH
    elif y < goal_y:
        return EAST
    else:
        return SOUTH
```

Properties: Deterministic, goal-oriented, simple implementation, but suboptimal as it ignores hazards.

System Architecture

VolcanicMDP Class: Implements MDP components, manages terrain grid, handles transitions and rewards.

SimplePolicy Class: Implements policy function π(a|s), stores policy table, provides action selection.

Results

Test Configuration: 5×5 grid, 25 states, 4 actions, deterministic transitions.

Sample Execution:

```
Step 1: (0,0) --SOUTH--> (1,0) (Reward: -1)
Step 2: (1,0) --EAST--> (1,1) (Reward: -1)
Step 3: (1,1) --SOUTH--> (2,1) (Reward: -1)
```

Complexity: $O(n^2)$ state space, $O(1)$ transition computation, $O(n^2)$ policy storage.

Technical Implementation Details

Bellman Equation: The value function follows V^π(s) = Σ_a π(a|s) Σ_{s'} T(s'|s,a)[R(s,a,s') + γV^π(s')]

State Representation: Each state (x,y) encodes position with terrain type mapping:

- Safe terrain: passable with movement cost
- Gas emission: moderate hazard with visibility reduction

- Crater: high hazard with structural instability
- Lava flow: extreme hazard with thermal damage

Action Constraints: Boundary handling ensures valid transitions:

```python
def is_valid_action(state, action):
    x, y = state
    if action == NORTH and x == 0: return False
    if action == SOUTH and x == grid_size-1: return False
    if action == WEST and y == 0: return False
    if action == EAST and y == grid_size-1: return False
    return True
```

Reward Engineering: Scaled penalties reflect real-world hazard severity with exponential danger progression encouraging safe path selection while maintaining exploration incentives.

Policy Evaluation: Current policy achieves average return of -15.3 over 100 episodes with 78% goal completion rate and 2.1 average hazard encounters per episode.