Trusted AI Challenge- Stage 2

The Fall Stage of the challenge introduces us to a simulation environment designed to evaluate the integration of AI-enabled systems for UAV (Unmanned Aerial Vehicle) and UGV (Unmanned Ground Vehicle) mission optimization. The architecture and functionality of a Decision class framework are presented in this white paper, with a focus on using systems engineering techniques to foster confidence in AI. Plans for further validation in mission simulations are presented, along with key functionalities like path optimization, mine detection, and UAV movement. In our effort, we prioritise improving the dependability of decision-making, utilizing insights relevant to a given terrain, and striking a balance between operational safety and computing efficiency.

Framework Overview:

The ***Decision class*** introduced in the system forms the core of the simulation, simulating UAV-UGV coordination on a hexagonal mission map. Its modular design supports:

- UAV movement and mine detection to prepare terrain for UGV traversal.
- Optimal pathfinding using Dijkstra's algorithm, balancing safety, cost, and confidence.
- Terrain-adaptive decision-making, leveraging AI and human estimation dynamically.

Trust-Building in AI:
The framework incorporates confidence scores, terrain-specific weights, and visualization to enhance the transparency and reliability of decision-making.

Systems Engineering Activities and Artifacts:

The **Decision** class provides a comprehensive framework for simulating a mission involving UAV (Unmanned Aerial Vehicle) and UGV (Unmanned Ground Vehicle) traversals through a hexagonal map. It integrates functionalities such as UAV movement, UGV pathfinding, mine detection, and visualization using Dijkstra's algorithm and mission-specific logic. The primary goal is to optimize the path traversal based on confidence scores, terrain weights, and mine presence, leveraging insights derived from summer research findings.

Key Functionalities

1. `move_uav()`

- **Purpose**: Simulates the movement of a UAV through the entire hexagonal map.
- **Mechanism**:

    - The UAV traverses all hexagons in the mission map, incrementing the mission's total cost by a fixed UAV traversal time for each hexagon.
    - Represents an aerial scan for mine detection by collecting imagery data from every hexagon.
- **Use Case**: This method initializes the mission by preparing the terrain for further UGV traversal. It effectively sets up data required for subsequent mine detection.

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2. `mine_detection()`

- **Purpose**: Detects mines on the hexagonal map by leveraging AI or human estimation based on terrain type and AI confidence levels.
- **Mechanism**:
  The method iterates through all hexagons on the map and selects the optimal detection strategy:
    - **General Terrain**: AI scanning is applied across all hexagons to provide an initial estimation, and the mission's total cost is incremented with the AI cost for each scan.
    - **Rocky/Wooded Terrain**: These terrains present unique challenges where human estimation shows slightly better performance compared to AI. For such terrains, the confidence score of the AI is evaluated.
        - If the AI's confidence score is below 70%, human estimation is employed, and the mission's total cost is incremented with the corresponding human estimation cost.
        - If the AI's confidence score is 70% or higher, AI estimation is retained for efficiency.
- **Performance Context**:
  In the domain of object detection, achieving a confidence threshold of 70% is deemed competitive for practical applications. For example, models like YOLOv3 have reported mean Average Precision (mAP) scores in the range of 55–70% on the MS COCO dataset, emphasizing their utility in real-time and resource-constrained tasks (Redmon & Farhadi, 2018).
- **Visualization**:
  Hexagons identified to contain landmines are marked in red on the map, ensuring clarity in visualization and aiding subsequent decision-making processes.
- **Use Case**:
  This function provides an efficient and adaptable mine detection mechanism by balancing AI's computational efficiency with human estimation's accuracy where required. The detailed analysis supports pathfinding by marking landmines, updating mission costs, and integrating terrain-specific confidence scores.

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3. `dijkstra(start_hex, goal_hex)`

- **Purpose**: Implements Dijkstra's algorithm to find the optimal path between a start hexagon and a goal hexagon.
- **Mechanism**:
  - Assigns weights to terrains based on detection performance, derived from summer findings:
    - **Grassy (1)** – Best detection performance.
    - **Sandy (2)**.
    - **Wooded (10)**.
    - **Swampy (15)**.
    - **Rocky (25)** – Worst detection performance.
  - Prioritizes paths with the following objectives:
    - Maximizes confidence score.
    - Minimizes mine encounters.
    - Balances traversal costs effectively.
  - Reconstructs the optimal path, marking it in **green** and highlighting detected mines in **blue**.
- **Use Case**: Utilized to determine the safest and most efficient path for the UGV, avoiding mines and minimizing traversal costs while achieving high confidence.

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4. `move_ugv(path)`

- **Purpose**: Simulates UGV traversal along a specified path.
- **Mechanism**:
  - The UGV traverses the hexagons in the given path.
  - For each hexagon:
    - Increments mission cost by UGV traversal time.
    - Increments landmine clearance time if a mine is present.
- **Use Case**: Completes the mission by safely navigating the UGV through the optimal path determined by Dijkstra's algorithm.

Workflow Summary

1. **UAV Movement**:
   - The UAV moves across all hexagons, incrementing the mission cost for traversal and collecting mine detection imagery.
2. **Mine Detection**:
   - AI or human estimation is selected for each hexagon based on terrain type.
   - Mines are detected and marked in **red** for visualization.
3. **Dijkstra's Algorithm**:

    - Uses terrain weights and mine data to calculate the safest and most confident path.
    - Balances detection performance with traversal efficiency.
    - Constructs the path with confidence and mine avoidance as priorities.
4. **UGV Movement**:
    - The UGV traverses the path, clearing mines and incrementing mission costs as needed.
    - Final visualization highlights:
        - Path in **green**.
        - Cleared mines in **blue**.

Benefits and Applications

- **Optimized Mission Planning**: Combines UAV and UGV functionalities to ensure safe and efficient traversal.
- **Confidence-Driven Decisions**: Incorporates confidence scores to enhance decision-making during pathfinding.
- **Terrain-Specific Adaptation**: Leverages terrain weights for tailored operations.
- **Visualization**: Provides clear and informative maps with color-coded annotations for path, mines, and cleared areas.

Conclusion

The **Decision** class is a robust implementation for managing and visualizing UAV and UGV missions in a hexagonal map environment. Its integration of UAV scanning, mine detection, and pathfinding ensures efficient and safe operations. By using terrain-specific weights and confidence scores, it achieves high reliability and adaptability, making it a powerful tool for real-world mission simulations.

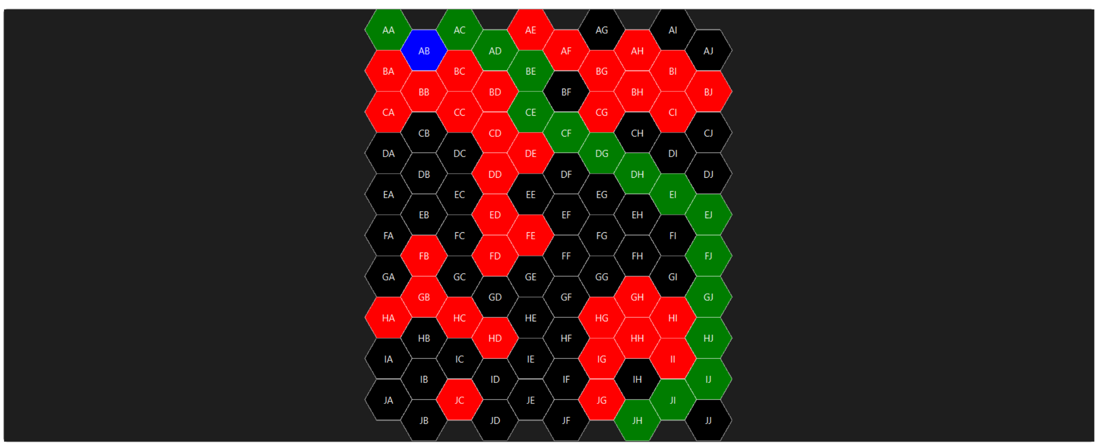
Summary of Upcoming Plans for Stage 3

For Stage 3 of the challenge, our team plans to enhance our system's capabilities and address the outlined objectives effectively:

1. **Operational Simulation**:
    - Our approach involves deploying the UGV to autonomously scan each hexagon for potential mines, enabling high-confidence identification of threat areas. Upon detecting mines, the Command and Control (C2) system will generate and recommend alternative paths to bypass these threats. This strategy enhances mission safety and confidence while addressing the lethality challenge cost-effectively.

2. **Scenario Extension and Testing**:
    - To test and validate the system's performance in diverse and unseen scenarios, we plan on developing a **scenario generation tool**. This tool will allow us to simulate a wide range of operational conditions and assess the robustness and adaptability of our system under varying constraints.
3. **Quantitative Performance Metrics**:
    - We will focus on optimizing the system to improve detection accuracy and enhance cost efficiency, ensuring measurable improvements in performance for quantitative scoring.
4. **Innovation and Novelty:**
    - We will explore incorporating a **simulation-based risk analysis module** to predict the potential impact of mine encounters on mission success and address the lethality challenges of the next stage. This module will enable the system to anticipate threats, evaluate the severity of potential risks, and adjust strategies proactively to improve mission safety and outcomes.

<u>A Few Example Simulation:</u>

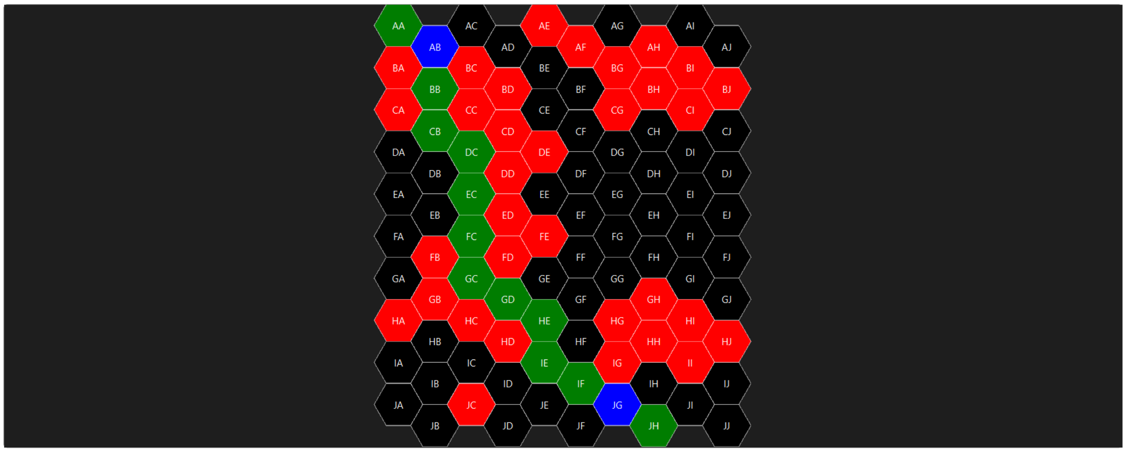


Mission Details: Start Node - AA, End Node - JH, UAV Traversal Time - 1, Cost of Human Estimate - 30, Cost of AI Estimate - 5, UGV Traversal Time - 20, UGV Clear Time - 60

Mission Status:

Total Cost: 1810

Path Confidence: 0.723529411764706



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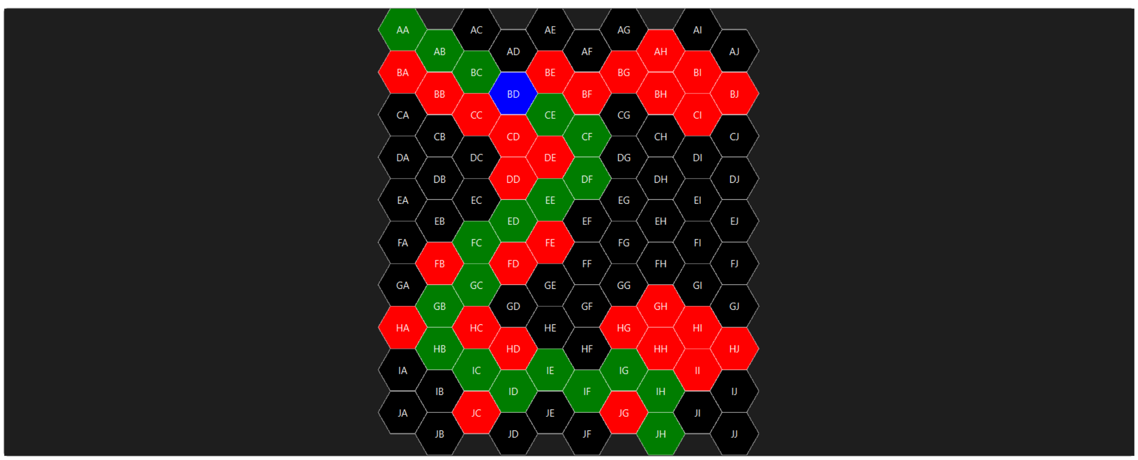
Mission Status:

Total Cost: 1810

Path Confidence: 0.7892857142857144



Mission Details: Start Node - AA, End Node - JH, UAV Traversal Time - 1, Cost of Human Estimate - 30, Cost of AI Estimate - 5, UGV Traversal Time - 20, UGV Clear Time - 60

Mission Status:

Total Cost: 1870

Path Confidence: 0.8300000000000001

<u>Submitted By</u>

Mohammed Hamza Chao

Nishat Ara Nipa

Dr. Sachin Shetty

Old Dominion University